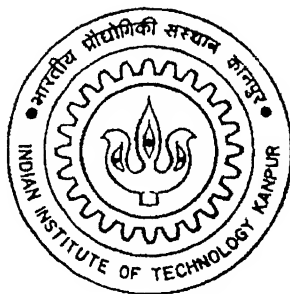


# CALIBRATION OF POTENTIAL FIELD FUNCTIONS OF THE POTENTIAL FIELD THEORY BASED MODEL OF DRIVER BEHAVIOR

*A Thesis Submitted*  
in Partial Fulfillment of the Requirements  
for the Degree of  
M.Tech

by  
**Ashish Mahajan**



*to the*  
**DEPARTMENT OF CIVIL ENGINEERING**  
**INDIAN INSTITUTE OF TECHNOLOGY KANPUR**  
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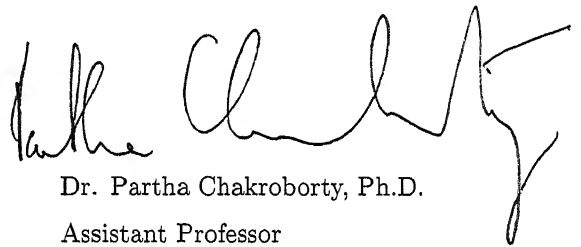
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## CERTIFICATE

*This is to certify that this M.Tech thesis work entitled **CALIBRATION OF POTENTIAL FIELD FUNCTIONS OF THE POTENTIAL FIELD THEORY BASED MODEL OF DRIVER BEHAVIOR** has been carried out by **Ashish Mahajan** under my supervision and it has not been submitted elsewhere for a degree.*

October 30, 2000



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Ashish Mahajan

[illegible]

Shri. B. K. Mahajan and Smt. Usha Mahajan

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## ABSTRACT

In recent time a single comprehensive model for driver behavior has been developed using potential field theory of the robot motion planning. These models, at present, do not have any mechanism for calibrating their parameters. In this thesis an attempt is made to develop a mechanism which can be used to calibrate the parameters of these models. Results using the proposed mechanism show that the proposed mechanism can form the ground work for the a larger and more extensive calibration mechanism for the potential field theory based model of driver behavior.

# Chapter 1

## INTRODUCTION

Microscopic models of traffic flow form the foundation for the theory of traffic flow. Microscopic models attempt to predict the drivers behavior in small interval of time. Driver behavior is captured in these models through to variables: (i) the steering angle chosen by driver, and (ii) the acceleration/deceleration rate use by the driver. Although, various microscopic models exist (Pipes [4], Forbes [5, 6], Chandler et al. [7], Herman et al. [8, 9], Gazis et al. [10, 11], Rockwell et al. [12], May and Keller [13], Kikuchi and Chakroborty [14], Chakroborty and Kikuchi [15], Taragin [16], Michaels and Gozan [17]) only two of them, namely, Vasishta [2] and Agrawal [1] attempt at developing a comprehensive model of driver behavior. That is, unlike the others, these models attempt to capture driver behavior in various driving situations (like, car-following, overtaking, free flow, etc) through a single model. These models are based on the potential field theory of robot motion planning (see Latombe [3]). However Vasishta [2] and Agrawal [1] do not suggest how various parameters of their model can be calibrated given data on observed driver behavior. This thesis attempts to overcome this short coming by developing a calibration algorithm.

The thesis is divided into six chapters of which this is the first. The second chapter describes the problem tackled here and lays down the scope of present thesis. The third chapter presents results from a detail parametric study of the potential field theory based models. The fourth chapter describes the proposed calibration mechanism. The fifth chapter presents the results obtained using proposed calibration mechanism for various different scenarios. The sixth and last chapter concludes this thesis by summarizing the achievement of this thesis and by discussing the short comings of the present work.

## Chapter 2

# PROBLEM STATEMENT AND SCOPE OF STUDY

In this thesis the problem of calibrating the parameters of potential field functions of potential field based theory model of traffic flow is studied. However, before presenting a detail description of problem and scope of study, a brief description of potential field theory based model of traffic flow is given.

### 2.1 Potential field theory based model

Vasishta [2] and Agrawal [1] have over last three years developed the potential field theory based model of traffic flow. This is a microscopic model which basically describe drivers' action in terms of steering angle choice and acceleration/deceleration choice under different driving scenarios. In this models a driving scenarios is defined as a conglomeration of traffic and roadway features in the immediate vicinity of a driver. Roadway feature, like road edges, curvature, potholes, etc, and traffic features, like parked vehicles, moving vehicles in the same and opposite direction, are all assumed to be obstacles which a driver avoid while driving. Each of these obstacle are assumed to emanate a repulsive force field around it. This force field is referred to as a potential field and is described mathematically through a potential field function.

The predicted actions of a driver, from this model, depends largely on the potential field functions of the obstacles. Despite this depends no attempt are made either by Vasishta [2] and

Agrawal [1] to develop the mechanism for calibrating the parameters of these functions. This lack of an available mechanism formed the motivation for this study.

## 2.2 Problem statement and scope of study

The problem here, as stated earlier is to develop a mechanism which can be used to calibrate the parameter of potential field functions. The mechanism should take as input the observed path of a driver in a real world situation and the predicted path from the model for the same situation with an initial assumed parameter values. The mechanism should produce as its output a set of calibrated parameter values which when used by the model produces the predicted path similar to the observed path.

In order to develop such a mechanism two tasks need to be accomplished. First, a study on the effect of different parameters on the predicted path need to be conducted. Second, based on the information available from this study, rules of calibration which tell us how to change the parameter values need to be developed. These tasks formed the subject matter of next two chapters.

Given the complex nature of potential field functions and the complex manner in which they affect the predicted path the scope of this study is kept limited. Basically in this study the scope is limited to calibrating the parameters of road edges and static obstacles likes potholes, parked vehicles, etc.

## Chapter 3

# PARAMETRIC STUDY OF POTENTIAL FUNCTIONS

As stated earlier, the tasks to be undertaken in this thesis are (i) to study the effect of potential field function parameter values on the driver's position profile and (ii) to develop an algorithms for modifying these parameters so that the predicted path emulates the observed path better. The first of these two tasks is the subject of this chapter. The chapter is divided into three sections. The first presents the potential field function for the obstacles (or driving features) which are considered in this thesis. The second and third sections present the effect of the parameters of the potential field functions.

### 3.1 Potential field functions for the different driving features

The driving features (i.e. roadway or traffic features) considered in this thesis are: (i) road edges and (ii) static obstacle (like potholes, parked vehicle etc). In this section the potential field function for these features as used by Vasishta [2] are presented. This is done so as to make the description of the parametric study complete.



### 3.1.1 Potential field function for road edges

The potential field function for a road edge is given by

$$U_e = ae^{-bz} \quad (3.1)$$

where,  $z$  is the distance from the road edge,  $a$  is a parameter which denotes the potential at the edge and  $b$  is a parameter which determines the rate of decrease of the potential with  $z$ . Specifically the function for the left edge,  $U_{LE}$ , and the right edge,  $U_{RE}$ , can be written as

$$U_{LE} = a_1 e^{-b_1 x} \quad (3.2)$$

and

$$U_{RE} = a_2 e^{-b_2(w-x)} \quad (3.3)$$

where,  $x$  is the distance from the left edge of the road;  $a_1$  and  $a_2$  are the potential values at the left edge and right edge respectively;  $b_1$  and  $b_2$  are the slope parameters for the left edge and right edge potential field functions respectively. The combined potential due to both the edges of the road,  $U_{be}$ , can be written as

$$U_{be} = a_1 e^{-b_1 x} + a_2 e^{-b_2(w-x)} \quad (3.4)$$

Note that it is meaningful to only work at  $U_{be}$  rather than then  $U_{RE}$  and  $U_{LE}$  since a road always has two edges. Further as suggested by Vasishta [2]

- $b_1 > 0, b_2 > 0$
- $a_2 > a_1$  ( because, in India drivers follow a “keep left” policy)

### 3.1.2 Potential field function for static obstacles

The potential field function for a static obstacle is given by

$$U_o = a_4 e^{-f(y)[(\frac{x-x_0}{m_1})^2 + (\frac{y-y_0}{m_a})^2 - 1] \rho} \quad (3.5)$$

where

$$\rho = \begin{cases} 1 & \text{if } (\frac{x-x_0}{m_1})^2 + (\frac{y-y_0}{m_a})^2 \geq 1 \\ 0 & \text{otherwise} \end{cases}$$

and

$$f(y) = \begin{cases} b_4 & \text{if } y \leq t_1 \\ \alpha y^3 + \beta y^2 + \gamma y + \delta & \text{if } t_1 < y < t_2 \\ b_5 & \text{if } y \geq t_2 \end{cases}$$

where  $(x, y)$  is the coordinate of any point on the road,  $(x_0, y_0)$  are the coordinates of the center of the obstacle;  $m_i$ ,  $m_a$  are respectively the semi-minor and the semi-major axes of the ellipse which circumscribes the obstacle;  $\rho$  is a boolean variable representing whether point  $(x, y)$  is inside the ellipse ( $\rho = 0$ ) or not ( $\rho = 1$ ). Further,  $a_4$  is the maximum value  $U_o$  can take and  $f(y)$  is a function which determines the slope for  $U_o$ .  $t_1$  and  $t_2$  are lower and upper limits of  $y$  with which  $f(y)$  varies.

Before leaving this section clarifications regarding (i) the determination of the coefficients of  $f(y)$  and (ii)  $m_i$  need to be given.

#### Clarification (i)

Given the value of  $b_4$ ,  $b_5$  and  $t_1$ ,  $t_2$  the coefficients  $\alpha, \beta, \gamma, \delta$  are calculated using the following restrictions: (i)  $f(y)$  should pass through  $(t_1, b_4)$  and  $(t_2, b_5)$ , and (ii)  $f(y)$  should pass through a point  $tp$  where its slope is also zero. Therefore, it needs to be noted that  $tp$  is also a parameter which affects the predicted path.

#### Clarification (ii)

The parameter  $m_i$  is not considered as a calibration parameter, since Vasishta [2] suggests a procedure for selection of  $m_i$  from the size and shape of an obstacle. Hence given the obstacle,  $m_i$  is fixed.

### 3.2 Effect of parameters of $U_{be}$ on the predicted driver path

The following are identified, as indicated by Vasishta [2], as parameters of  $U_{be}$ :  $a_1$ ,  $a_2$ ,  $b_1$  or  $b_2$  and  $\frac{b_1}{b_2}$ . The effect of these parameters on the predicted path is studied here.

#### Effect of $a_1$

Figure 3.1 shows the effect of  $a_1$  on predicted driver path on a 6 m road keeping all other parameters as constant ( $a_2 = 4.0$ ,  $b_1 = 0.32641$ ,  $b_2 = 0.04663$  and  $\frac{b_1}{b_2} = 7.0$ ). It can be seen that, when the value of  $a_1$  increases the predicted path shifts towards right edge of the road. The same behavior can be observed from other road widths also.

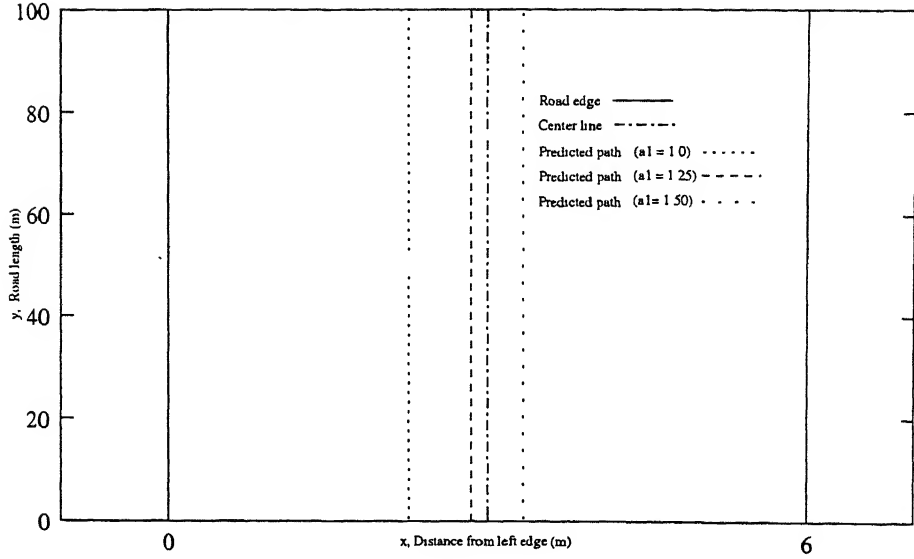


Figure 3.1: Effect of  $a_1$

### Effect of $a_2$

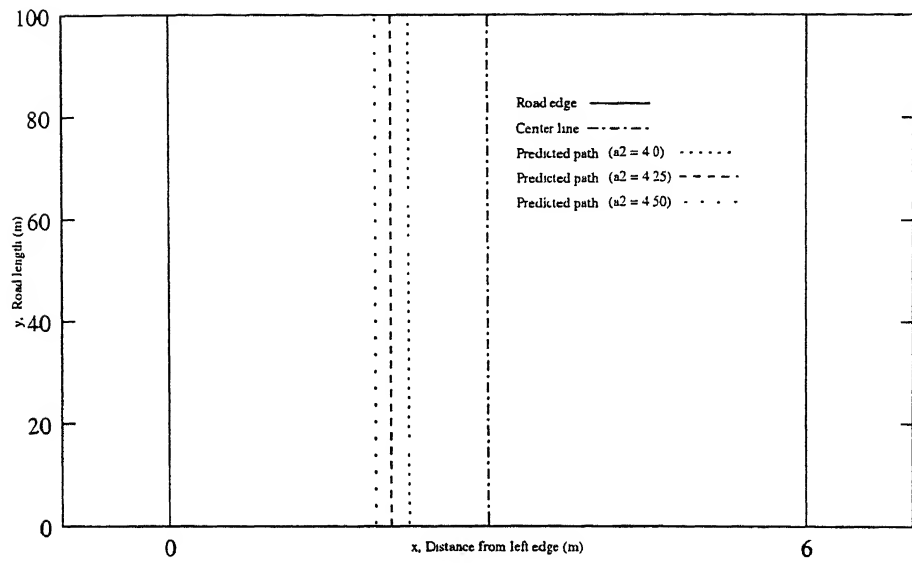
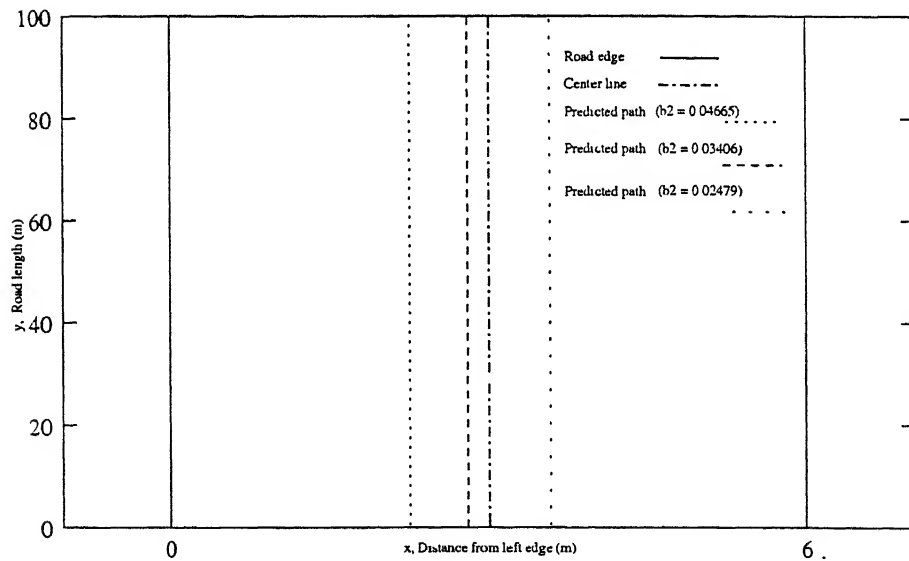
Figure 3.2 shows the effect of  $a_2$  on predicted driver path on a 6 m road keeping all other parameters as constant ( $a_1 = 1.0$ ,  $b_1 = 0.32641$ ,  $b_2 = 0.04663$  and  $\frac{b_1}{b_2} = 7.0$ ). It can be seen that, when the value of  $a_2$  increases path shifts towards left edge of the road. The same behavior can be observed from other road widths also.

### Effect of $b_1$ or $b_2$

Figure 3.3 shows the effect of  $b_2$  on driver path on a 6 m road keeping ratio of  $\frac{b_1}{b_2}$  and all other parameters as constant ( $a_1 = 1.0$ ,  $a_2 = 4.0$  and  $\frac{b_1}{b_2} = 7.0$ ). It can be seen that, when the value of  $b_2$  increases the predicted path shifts towards left edge of the road. It should be noted that keeping  $\frac{b_1}{b_2}$  constant and changing  $b_2$  also implies changing  $b_1$  in the same direction (i.e. increasing  $b_2$  implies increasing  $b_1$ ). Similar behavior can be observed for different road widths and  $\frac{b_1}{b_2}$  ratio.

### Effect of $\frac{b_1}{b_2}$

The effect of this can not be studied separately from effect of  $b_1$  or  $b_2$  because changing  $\frac{b_1}{b_2}$  implies a change in  $b_1$  or  $b_2$ . Hence no clear direction in the shift of the predicted path can be observed by changing  $\frac{b_1}{b_2}$ . Hence no result is presented here. As will be seen later, knowledge of the effect of  $\frac{b_1}{b_2}$  is not crucial to development of the calibration algorithms— the primary purpose of the thesis.

Figure 3.2: Effect of  $a_2$ Figure 3.3: Effect of  $b_2$

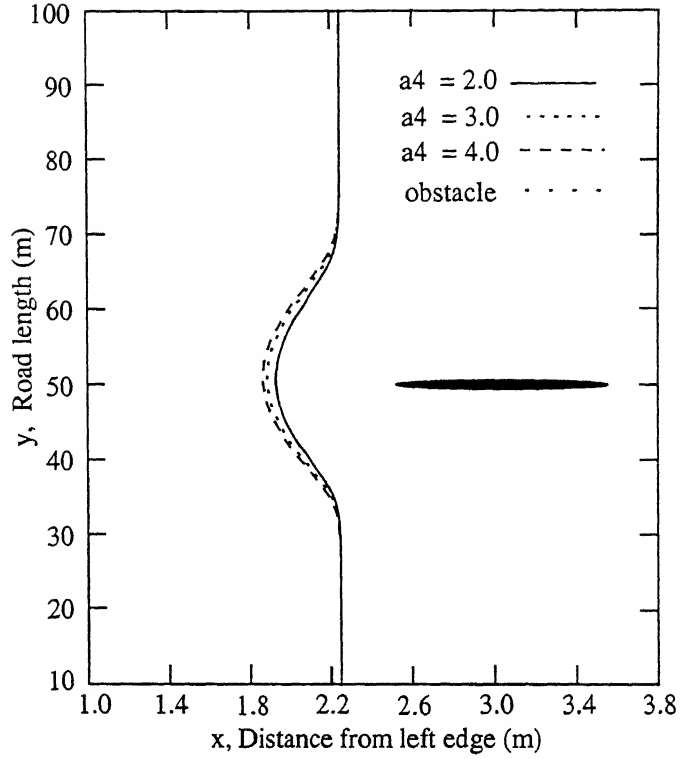


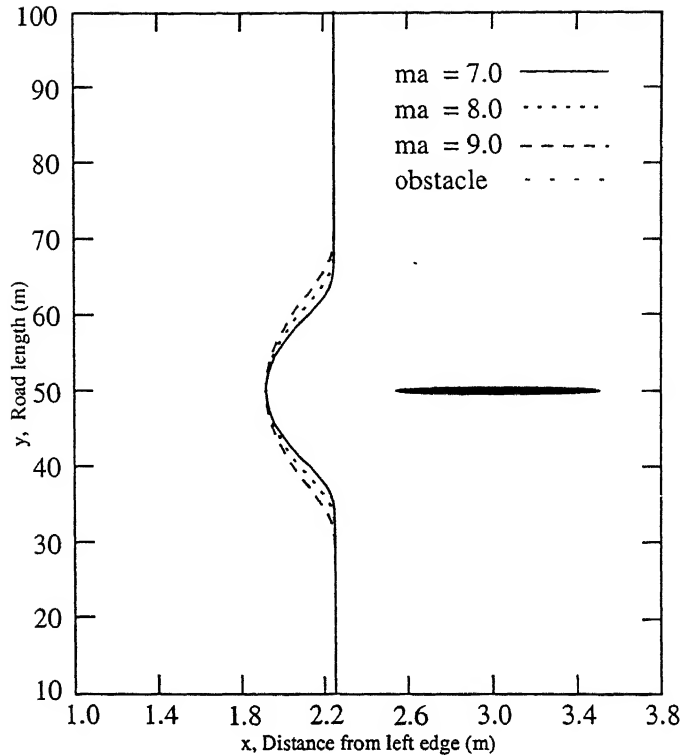
Figure 3.4: Effect of  $a_4$

### 3.3 Effect of parameters of $U_o$ on predicted driver path

The following are identified as parameters of  $U_o$ :  $a_4$ ,  $m_a$ ,  $b_4$ ,  $b_5$ ,  $tp$ ,  $t_1$ , and  $t_2$ . The effect of these parameters on the predicted path are studied here.

#### Effect of $a_4$

Figure 3.4 shows the effect of  $a_4$  on the predicted driver path on a 6 m road keeping all other parameters as constant. The value of the other parameters for the predicted paths in Figure 3.4 are: (i) edge potential function parameters,  $a_1 = 1.0$ ,  $a_2 = 4.0$ ,  $b_1 = 0.32641$ ,  $b_2 = 0.04663$  and (ii) obstacle potential function parameters,  $m_i = 0.5$ ,  $m_a = 9.0$ ,  $b_4 = 2.0$ ,  $b_5 = 2.0$ ,  $\alpha = 0$ ,  $\beta = 0$ ,  $\gamma = 0$ ,  $\delta = 2.0$ ,  $t_1 = 20$ ,  $t_2 = 80$  and  $tp = (2, 50)$ . It can be seen that when  $a_4$  increases the deviation in the transverse direction (i.e. direction along the width) as well as deviation in the longitudinal direction (i.e. direction along the length) increase. Further, the effect is symmetrical about a transverse axis through the center of the obstacle. Also note that effect in the longitudinal direction is lesser than in the transverse direction.

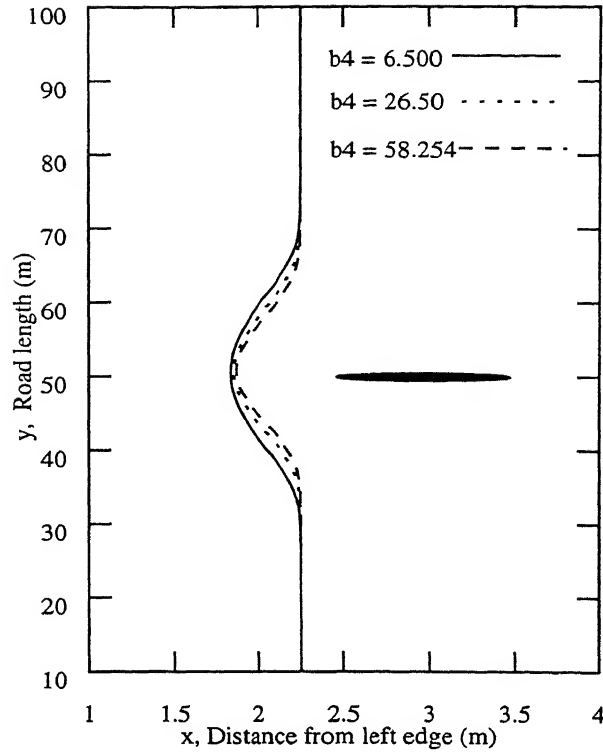
Figure 3.5: Effect of  $m_a$ 

#### Effect of $m_a$

Figure 3.5 shows the effect of  $m_a$  on the predicted driver path on a 6 m road keeping all other parameters as constant. The values of the other parameters for the predicted paths in Figure 3.5 are: (i) edge potential function parameters,  $a_1 = 1.0$ ,  $a_2 = 4.0$ ,  $b_1 = 0.32641$ ,  $b_2 = 0.04663$  and (ii) obstacle potential parameters,  $a_4 = 4.0$ ,  $m_i = 0.5$ ,  $b_4 = 2.0$ ,  $b_5 = 2.0$ ,  $\alpha = 0$ ,  $\beta = 0$ ,  $\gamma = 0$ ,  $\delta = 2$ ,  $t_1 = 20$ ,  $t_2 = 80$  and  $tp = (2, 50)$ . It can be seen that, when  $m_a$  increases the transverse deviation (along the width of road) as well as deviation in the longitudinal (i.e. direction along the length) increase. However, the effect in longitudinal direction pronounced then in lateral direction; in fact, the maximum transverse deviation is insensitive to  $m_a$  value. Further, the deviations are symmetric about a transverse axis through the center of the obstacle.

#### Effect of $b_4$

Figure 3.6 shows the effect of  $b_4$  on a 6 m road keeping all other parameters as constant. The values of the other parameters for the predicted paths in Figure 3.6 are: (i) edge potential function

Figure 3.6: Effect of  $b_4$ 

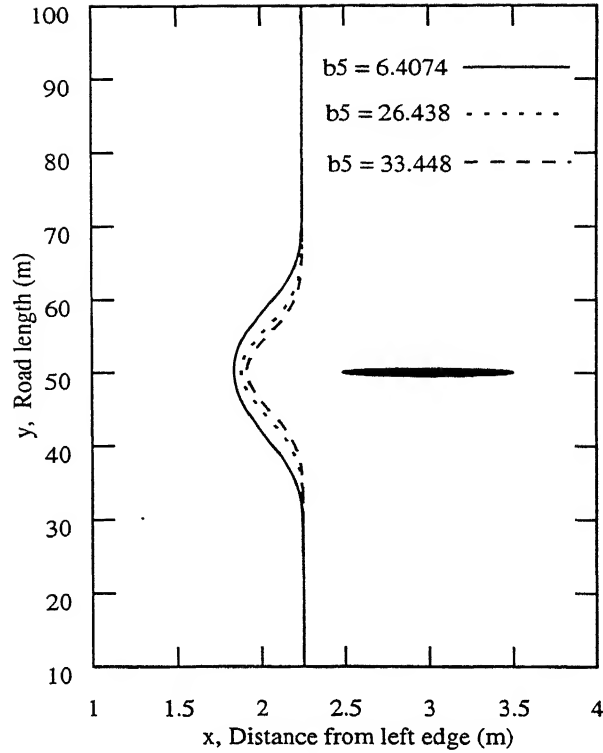
parameters,  $a_1 = 1.0$ ,  $a_2 = 4.0$ ,  $b_1 = 0.032641$ ,  $b_2 = 0.04663$  and (ii) obstacle potential function parameters,  $a_4 = 2.0$ ,  $m_i = 0.5$ ,  $m_a = 8.0$ ,  $t_1 = 10.0$ ,  $b_5 = 2.5$ ,  $t_2 = 80.0$  and  $tp = (50, 1.5)$ . It can be seen that, when the value of  $b_4$  increases the transverse and longitudinal deviation on both side of  $tp$  decrease. The decrease, is however least at  $y = 50$ , the abscissa value for  $tp$ .

#### Effect of $b_5$

Figure 3.7 shows the effect of  $b_5$  on 6 m a road keeping all other parameters as constant. The values of the other parameters for the predicted paths in Figure 3.7 are: (i) edge potential function parameters,  $a_1 = 1.0$ ,  $a_2 = 4.0$ ,  $b_1 = 0.032641$ ,  $b_2 = 0.04663$  and (ii) obstacle potential function parameters,  $a_4 = 2.0$ ,  $m_i = 0.5$ ,  $m_a = 8.0$ ,  $b_4 = 2.50$ ,  $t_1 = 20$ ,  $t_2 = 75$  and  $tp = (50, 1.5)$  It can be seen that, when  $b_5$  increases transverse and longitudinal deviation on both side of  $tp$  decrease. The decrease, is however least at  $y = 50$ , the abscissa value for  $tp$ .

#### Effect of $tp$

In order to study the effect of  $tp$  six cases are constructed. These are described in following table

Figure 3.7: Effect of  $b_5$ Table 3.1: Cases for studying  $tp$ 

<i>abscissa of <math>tp</math></i>	<i>ordinate of <math>tp</math></i>		
	<i>below <math>b_4</math> and <math>b_5</math></i>	<i>above <math>b_4</math> and <math>b_5</math></i>	<i>in between <math>b_4</math> and <math>b_5</math></i>
above the $y$ coordinate of obstacle	Case I	Case III	Case V
below the $y$ coordinate of obstacle	Case II	Case IV	Case VI

The specific details of the cases and their corresponding figures are given below.

### Cases I and II

Figure 3.8 shows five paths, each for a different value of the abscissa of  $tp$ . The obstacle is at (3, 50), hence, two of the paths are for values which place the  $tp$  above the  $y$  coordinate of obstacle (case I), two of the paths are for values which place the  $tp$  below the  $y$  coordinate of obstacle (case II), and one path is when the  $tp$ 's abscissa value equal to the  $y$  coordinate of the obstacle. All the paths are plotted for the following parameter values: (i) edge potential function parameters,  $a_1 = 1.0$ ,  $a_2 = 4.0$ ,  $b_1 = 0.032641$ ,  $b_2 = 0.04663$  and (ii) obstacle potential function parameters,  $a_4 = 2.0$ ,  $m_i =$



0.5,  $m_a = 8.5$ ,  $b_4 = 3.00$ ,  $t_1 = 0.0$ ,  $b_5 = 3.0$ ,  $t_2 = 100.0$ . It can be seen from figure that as  $tp$  moves away from the  $y$  coordinate of obstacle. The deviation reduce, irrespective of whether  $tp$  is above or below the position of the obstacle.

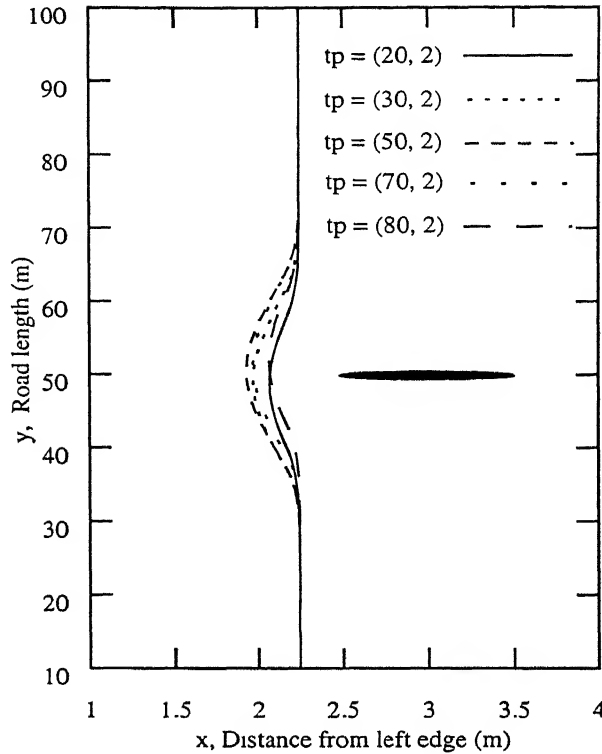


Figure 3.8: Effect of  $tp$  in Cases I and II

### Cases III and IV

Figure 3.9 shows the five paths, each for a different value of the abscissa of  $tp$ . The obstacle is at  $(3, 50)$ , hence, two of the paths are for values which place the  $tp$  above the  $y$  coordinate of obstacle (Case III), two of the paths are for values which place the  $tp$  below the  $y$  coordinate of obstacle (case IV) and one path is when the  $tp$ 's abscissa value equal to the  $y$  coordinate of the obstacle. All the paths are plotted for the following parameter values: (i) edge potential function parameters,  $a_1 = 1.0$ ,  $a_2 = 4.0$ ,  $b_1 = 0.032641$ ,  $b_2 = 0.04663$  and (ii) obstacle potential function parameters,  $a_4 = 2.0$ ,  $m_z = 0.5$ ,  $m_a = 8.5$ ,  $b_4 = 3.00$ ,  $t_1 = 0.0$ ,  $b_5 = 3.0$ ,  $t_2 = 100.0$ . It can be seen from figure that as  $tp$  moves away from the  $y$  coordinate of obstacle. The deviation increase, irrespective of whether  $tp$  is above or below the position of the obstacle.

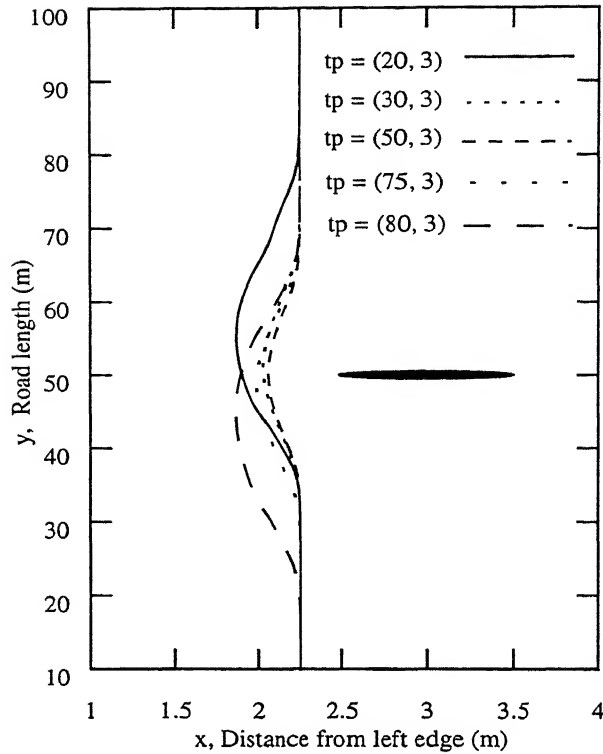
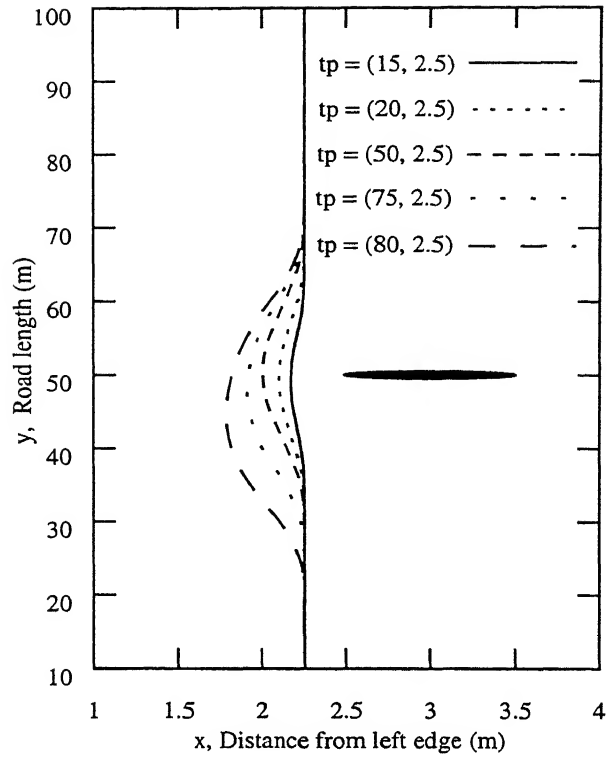
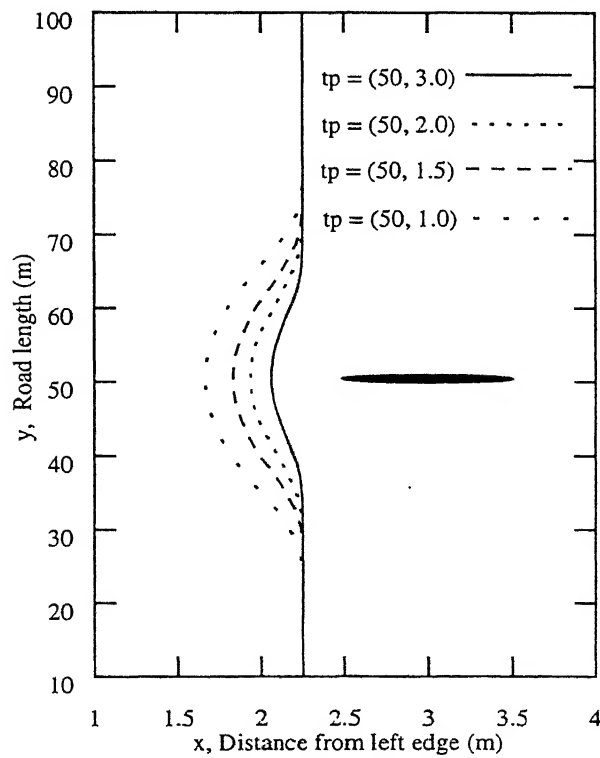


Figure 3.9: Effect of  $tp$  in Cases III and IV

### Cases V and VI

In these Cases, the ordinate of  $tp$  is in between  $b_4$  and  $b_5$ . For the same reasons as above five paths are plotted and shown in Figure 3.10. Each of these paths are plotted for the following parameter values: (i) edge potential function parameters,  $a_1 = 1.0$ ,  $a_2 = 4.0$ ,  $b_1 = 0.32641$ ,  $b_2 = 0.04663$  and (ii) obstacle potential parameters,  $a_4 = 2.0$ ,  $m_i = 0.5$ ,  $m_a = 8.5$ ,  $b_4 = 3.50$ ,  $t_1 = 0.0$ ,  $b_5 = 1.5$ ,  $t_2 = 100.0$ . It can be observed from the Figure 3.10 that if the obstacle of  $tp$  is on the same side of the obstacle as the lesser of  $b_4$  and  $b_5$  (in this case  $b_4 < b_5$ ) [notice here that  $b_4$  is the slope on the upstream side of obstacle and  $b_5$  is the slope on the downstream side of obstacle] then as  $tp$  moves away from obstacle the deviations increase. If, however  $tp$  is on the same side of obstacle as the greater of  $b_4$  and  $b_5$  (in this case  $b_5$ ) then as  $tp$  moves away from the obstacle the deviations decrease.

Another aspect, which needs to be pointed out here is the effect of only changing the ordinate of  $tp$  keeping all other parameters fixed. Figure 3.11 shows four paths. Each is drawn for a different value of the ordinate. As can be seen, from the figure, the deviation decrease as the ordinate value

Figure 3.10: Effect of  $tp$  in Cases V and VIFigure 3.11: Effect of ordinate of  $tp$

increases, irrespective of whether they are greater or smaller than  $b_4$  and  $b_5$ .

### Effect of $t_1$

Figure 3.12 shows the effect of  $t_1$  on the predicted path of driver on a 6 m road keeping all other parameters as constant. The values of the other parameters for the predicted paths in Figure 3.12 are: (i) edge potential function parameters,  $a_1 = 1.0$ ,  $a_2 = 4.0$ ,  $b_1 = 0.32641$ ,  $b_2 = 0.04663$  and (ii) obstacle potential parameters,  $a_4 = 2.0$ ,  $m_i = 0.5$ ,  $m_a = 8.5$ ,  $b_4 = 1.9$ ,  $b_5 = 1.9$ ,  $t_2 = 85.0$  and  $tp = (50, 3)$ . It can be seen that, when  $t_1$  moves away from the obstacle lateral and longitudinal deviations in the paths increase, although minimally.

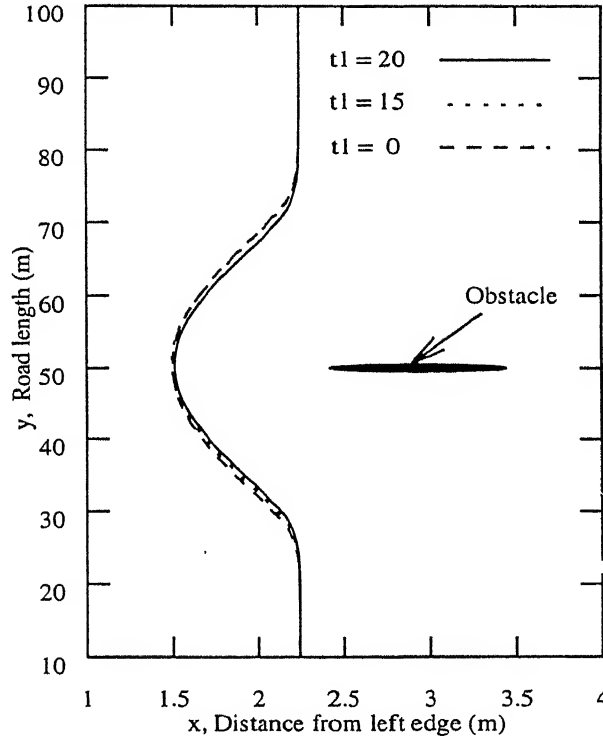


Figure 3.12: Effect of  $t_1$

### Effect of $t_2$

Figure 3.13 shows the effect of  $t_2$  on the predicted path of driver on a 6 m road keeping all other parameter as constant. The values of the other parameters for the predicted paths in Figure 3.13 are: (i) edge potential function parameters,  $a_1 = 1.0$ ,  $a_2 = 4.0$ ,  $b_1 = 0.32641$ ,  $b_2 = 0.04663$  and (ii) obstacle potential parameters,  $a_4 = 2.0$ ,  $m_i = 0.5$ ,  $m_a = 8.5$ ,  $b_4 = 1.90$ ,  $t_1 = 0.0$ ,  $b_5 = 1.9$  and

$tp = (50, 3)$ . It can be seen that, when  $t_2$  moves away from the obstacle deviations in the paths increase, although minimally.

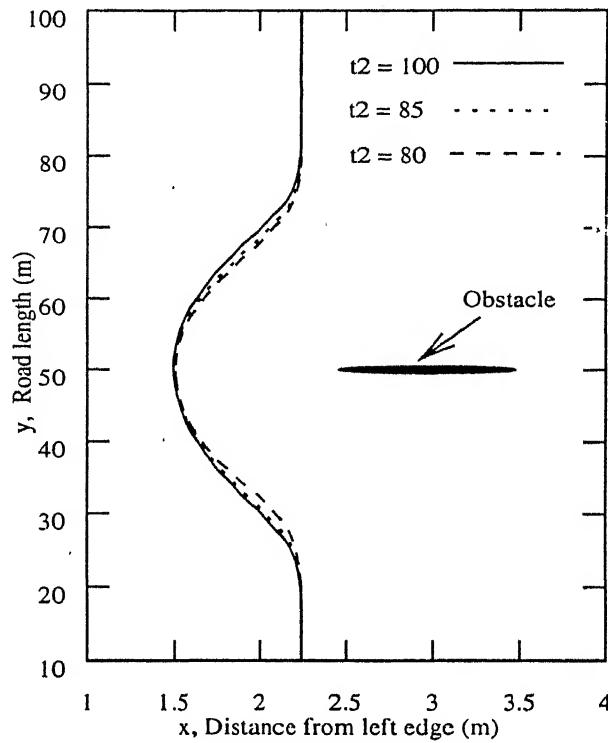


Figure 3.13: Effect of  $t_2$

Based on the above parametric study, few important points relevant to the calibration process emerge.

1. The parameters of the potential functions changes the predicted path in a variety of ways. Thus, it is felt that one can modify an initially predicted path to the observed path by varying these parameters.
2. Further, it is possible to determine a direction of change of certain parameters given the observed and initially predicted path. For example, if the observed path lies to the left of the initially predicted path one can find that  $a_1$  has to be decrease,  $a_2$  has to be increase etc.
3. There are however certain parameters for which it is not possible to predict any such direction of change.
4. Lastly, one could identify certain parameters such as,  $t_1$  and  $t_2$ , which do not affect the predicted path much.

## Chapter 4

# PROPOSED CALIBRATION PROCESS

In this chapter the proposed procedure for calibration are described. The chapter is divided into three sections in the first section overview of the proposed calibration procedure is explained. Section two describes Stage I of calibration procedure. Section three describes Stage II of calibration procedure.

### 4.1 Overview of the proposed calibration procedure

Given the observed path and the initial path (obtained using an initial set of values for the parameters of the potential field theory model) the calibration procedure uses the following steps to calibrate the parameter values of the potential field functions.

1. Plot the initial path and observed path on a Cartesian space with abscissa,  $x$ , as the distance from the left edge of the road and ordinate,  $y$ , as the distance along the road from some arbitrary location.
2. Divide the length of the road into a number of cross-sections (i.e. section with same ordinate). The cross sections can be arbitrarily close.
3. For a cross section  $i$ , determine the error  $E_i$  as follows:

$$E_i = |(X_{obs}^i - X_{in}^i)| \quad (4.1)$$

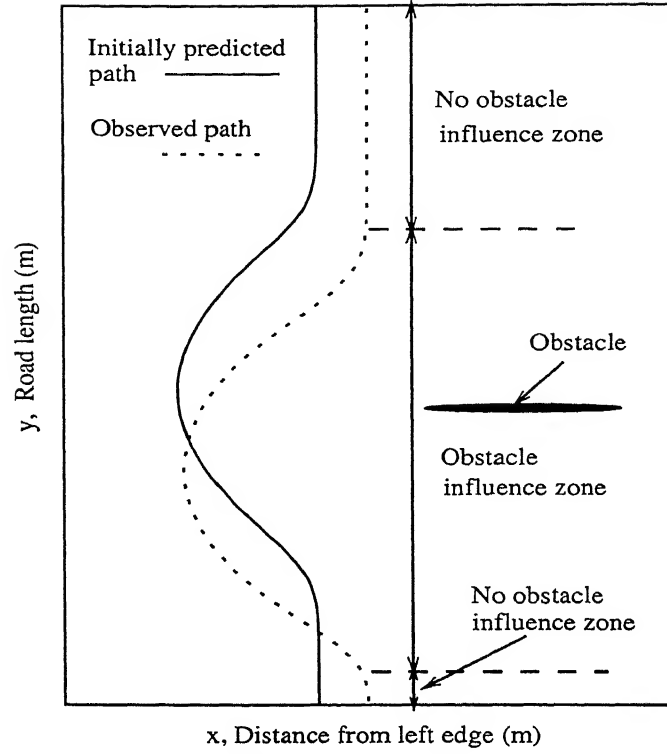


Figure 4.1: Stretch of the road illustrating the initially predicted path and the observed path

where  $E_i$  is the absolute error at  $i^{th}$  cross-section of the road,  $X_{obs}^i$  and  $X_{in}^i$  are the abscissa of observed and initial paths respectively at the  $i^{th}$  cross-section.

4. Check whether the  $E_i$  at each cross-section is less than some threshold limit; if not, then correction in parameters of potential functions are required so go to next step; if yes, stop the process.
5. Determine  $E_i$  in the no-obstacle influence zone (see the Figure 4.1 for the definition of no-obstacle influence zone).
6. Check whether the  $E_i$  in the no-obstacle influence zone is less than the threshold limit; if no, apply Stage I of calibration procedure (as explained in Section 4.2); if yes, determine the characteristics of the observed path relative to the initial path after Stage I of calibration (as explained in Section 4.3) and apply Stage II correction rules to modify the parameter values of obstacle potential field function (as explained in Section 4.3.2).
7. Replot initial path with modified (corrected) parameters of the potential functions and go to Step 2. These steps are shown schematically in Figure 4.2.

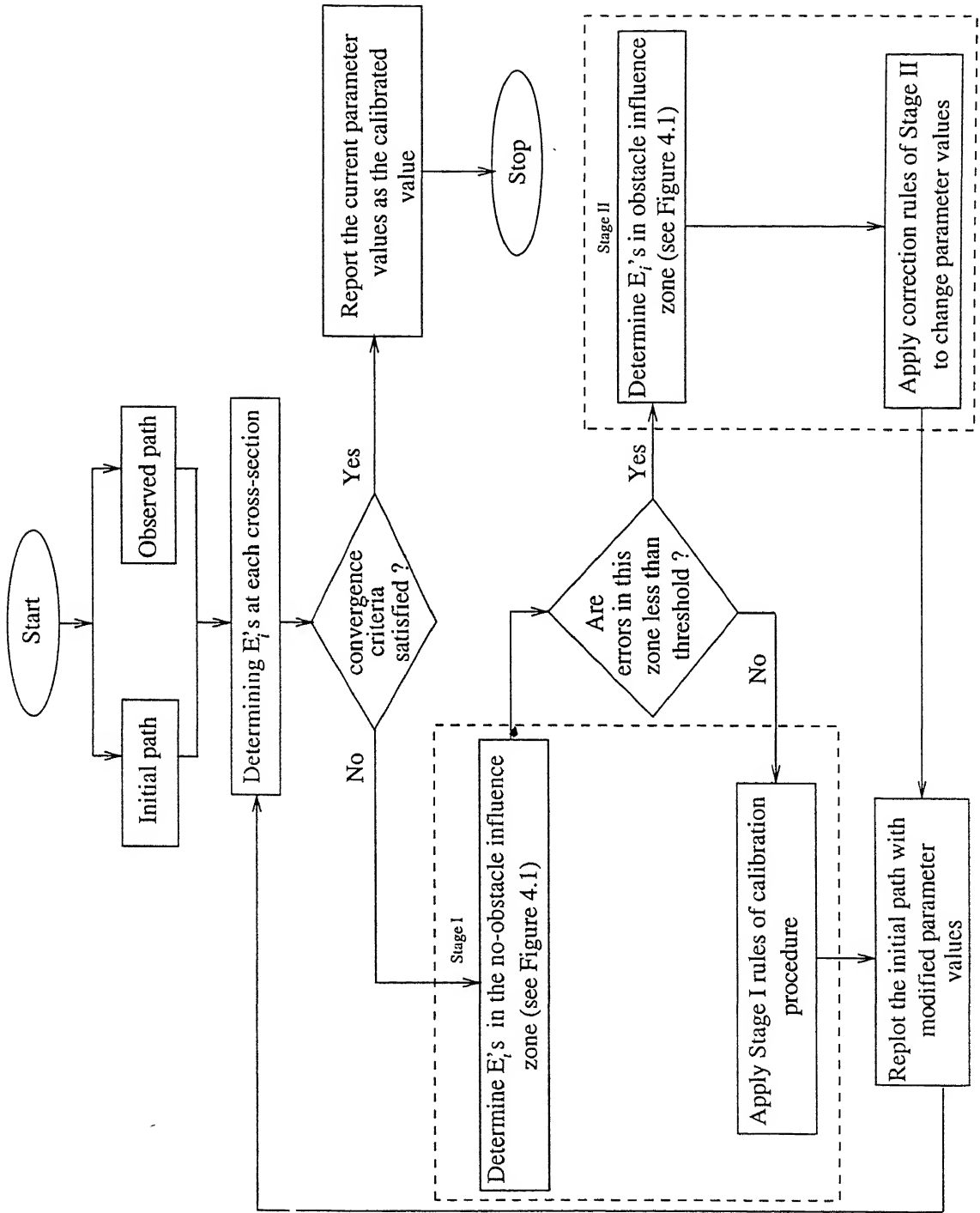


Figure 4.2: Overview of the proposed calibration procedure



## 4.2 Calibration procedure for Stage I

In Stage I, the corrections are applied to the parameters of the road edge potential functions to remove the errors in the no-obstacle influence zone (see the Figure 4.1 for the definition of no-obstacle influence zone) since in this zone only edge potential functions are active. The algorithm for Stage I corrections is based on the study performed in Chapter 3 on the effect of different parameters on the predicted path. As can be seen, from the study varying different parameters do have similar effects on the predicted path. For example, the predicted path shifts towards the right edge if  $a_1$  is increased or  $a_2$  is decreased, etc. Also, it can be observed that the rate of change of the predicted path with respect to different are different. Based on these observation, the algorithm is formulated thus:

1. Determine  $X_{obs}^i$  and  $X_{in}^i$  at  $i^{th}$  cross-section of road in no-obstacle influence zone.
2. Determine absolute error at  $i^{th}$  cross-section in no-obstacle influence zone,  $E_i$ , as given below.

$$E_i = |(X_{obs}^i - X_{in}^i)| \quad (4.2)$$

3. Check whether  $E_i$  is less than threshold, if no, the correction in edge potential field function is required so go to next step; if yes, no correction is required so stop the process.
4. If  $X_{obs}^i > X_{in}^i$  increase  $a_1$  and decrease  $a_2$  (or if  $X_{obs}^i < X_{in}^i$  decrease  $a_1$  and increase  $a_2$ ) with small step size without violating the following condition:  $a_2 > a_1$ ; and  $a_2 e^{-b_2 w} + a_1 < a_1 e^{-b_1 w} + a_2$ .
5. Either increase or decrease the value of  $b_2$  with small step size (keeping in mind the conditions:  $a_2 > a_1$ ; and  $a_2 e^{-b_2 w} + a_1 < a_1 e^{-b_1 w} + a_2$ ) so that error calculated by Equation 4.2 is further reduced and check whether error is less than threshold limit if yes, stop the procedure; if not, go to next step. Here, both increase and decrease of  $b_2$  is tried because the position of the path also depends on  $\frac{b_1}{b_2}$  and as such a clear understanding of the effect of  $b_2$  alone is not available.
6. Either increase or decrease the value of  $b_1$  (keeping in mind the conditions:  $a_2 > a_1$ ; and  $a_2 e^{-b_2 w} + a_1 < a_1 e^{-b_1 w} + a_2$ ) with small step size so that error calculated by Equation 4.2 further reduce and check whether it is less than threshold limit if not, go to Step 4. Here, both increase and decrease of  $b_1$  is tried because the position of the path also depends on  $\frac{b_1}{b_2}$  and as such a clear understanding of the effect of  $b_1$  alone is not available.

After applying Stage I corrections, in theory, the predicted path and the observed path in the no obstacle influence zone should become indistinguishable. Figure 4.3 shows a schematic of how the predicted would be in comparison to the observed path before and after Stage I calibrations.

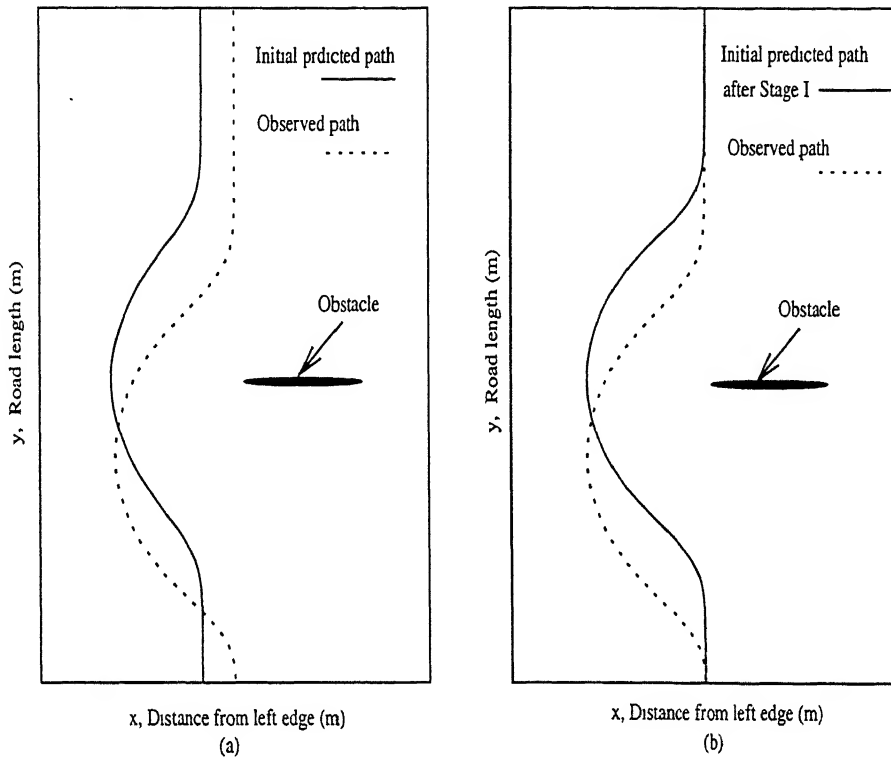


Figure 4.3: (a) Comparison of predicted path and observed path (a) before Stage I calibration and (b) after Stage I Calibration

### 4.3 Calibration procedure for Stage II

In stage two, corrections are applied to the parameters of obstacle potential field function. The calibration procedure can be divided into two parts:

1. Measurement of characteristics of predicted path relative to observed path in obstacle influence zone after the completion of Stage I calibrations.
2. Application of the rules of correction developed here to the parameters of the obstacle potential field function.

#### 4.3.1 Measurement of characteristics of predicted path after Stage I relative to observed path.

The characteristics of the predicted path are measured in terms of the following factors:

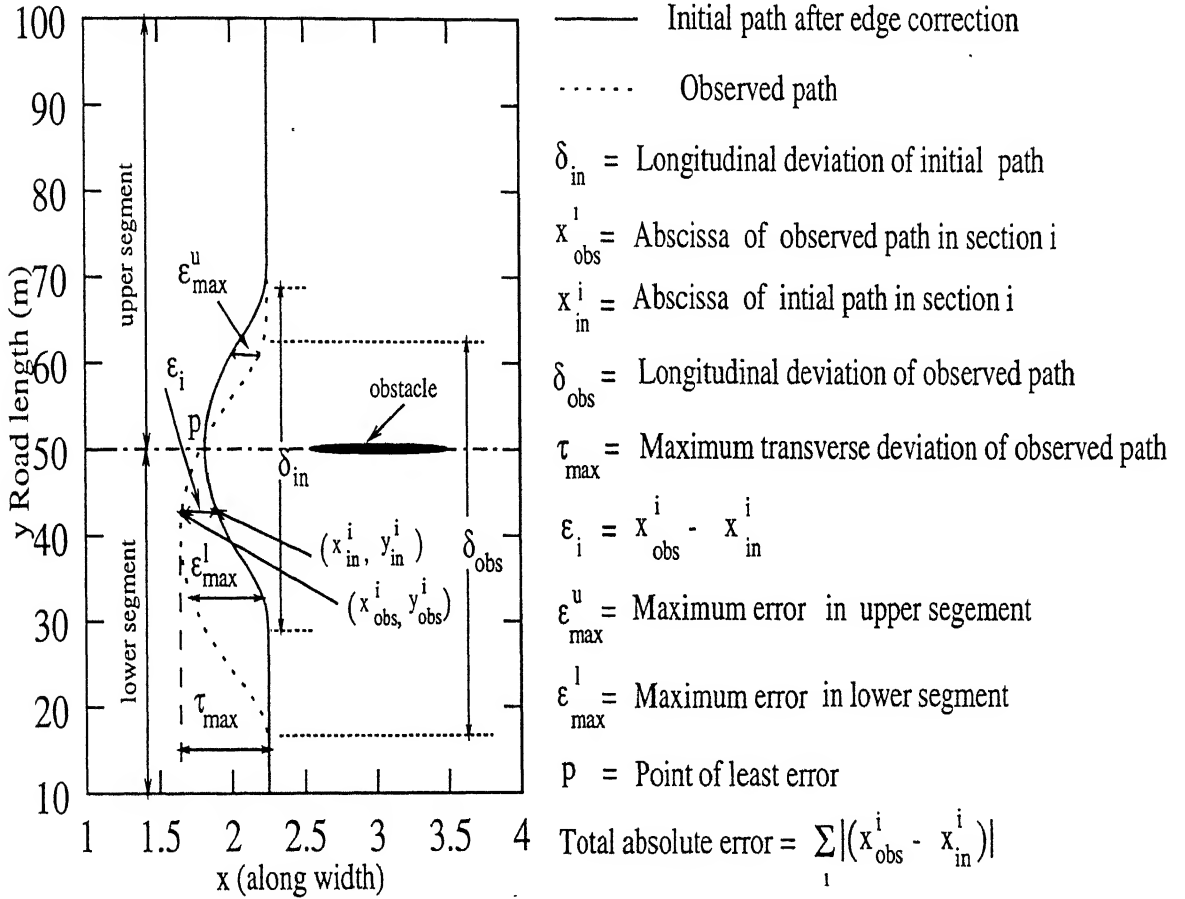


Figure 4.4: Illustration of the characteristics of the observed path and predicted path after Stage I calibration

1. Position of predicted path relative to observed path in a number of transverse sections in the obstacle influence zone.
2. Total absolute error between observed and predicted path obtained using:  
 Total absolute error =  $\sum_{i=1}^n |(X_{obs}^i - X_{in}^i)|$ , where "i" is a transverse section.
3. Maximum transverse deviation of observed path and predicted path and their location along the road stretch consider(see Figure 4.4).

4. Longitudinal deviation of observed path and predicted path (see Figure 4.4).
5. The point of least error (see Figure 4.4).
6. Maximum error in the upper part of the path and maximum error in lower part of the path.

These characteristics are measured in order help classify a particular scenario so that proper corrective actions can be taken. In the next section various scenarios (i.e. predicted path in comparison to observed path) are identified and the appropriate corrective actions in each of these cases are described.

### 4.3.2 Correction rules for the parameters of potential field function of obstacles

In this section the rules for the calibration of the parameter of the potential field function of static obstacle are presented. On studying the problem it was realized that a generalized calibration mechanism may not be feasible due to the complex nature of potential function and the way the parameters affect the path. Hence, it was decided to first classify a given condition (i.e., a given combination of the initially predicted path and the observed path) in to different "Situations." The classification is based on the characteristics define in the earlier section. However, for clarity of understanding the different situation are presented here schematically in Figure 4.5.

#### Classifications

In all the parts of the figure the vehicle is assumed to travel from bottom to top of the figure. Part (a) of the figure is referred to as Situation 1. In this situation the initial path lies totally to the left of the observed path. That is, both the transverse and longitudinal deviation of initial path are more than that of the observed path. Part (b) of the figure is referred to as Situation 2. In this situation the initial path lies completely to the right of observed path. Part (c) of the figure is referred to as Situation 3. In this situation the initial path intersect the observed path. Further, the initial path is farther from the obstacle in the upstream side of the obstacle and closer to the obstacle in the downstream side of the obstacle when compared to the observed path. Part (d) of the figure is Situation 4 and represents the exact opposite of Situation 3. Part (e) of the figure represents Situation 5. In this situation the initial path intersect the observed path twice. Further, the initial path is farther than the observed path in the vicinity of obstacle. Part (f) of the figure referred as

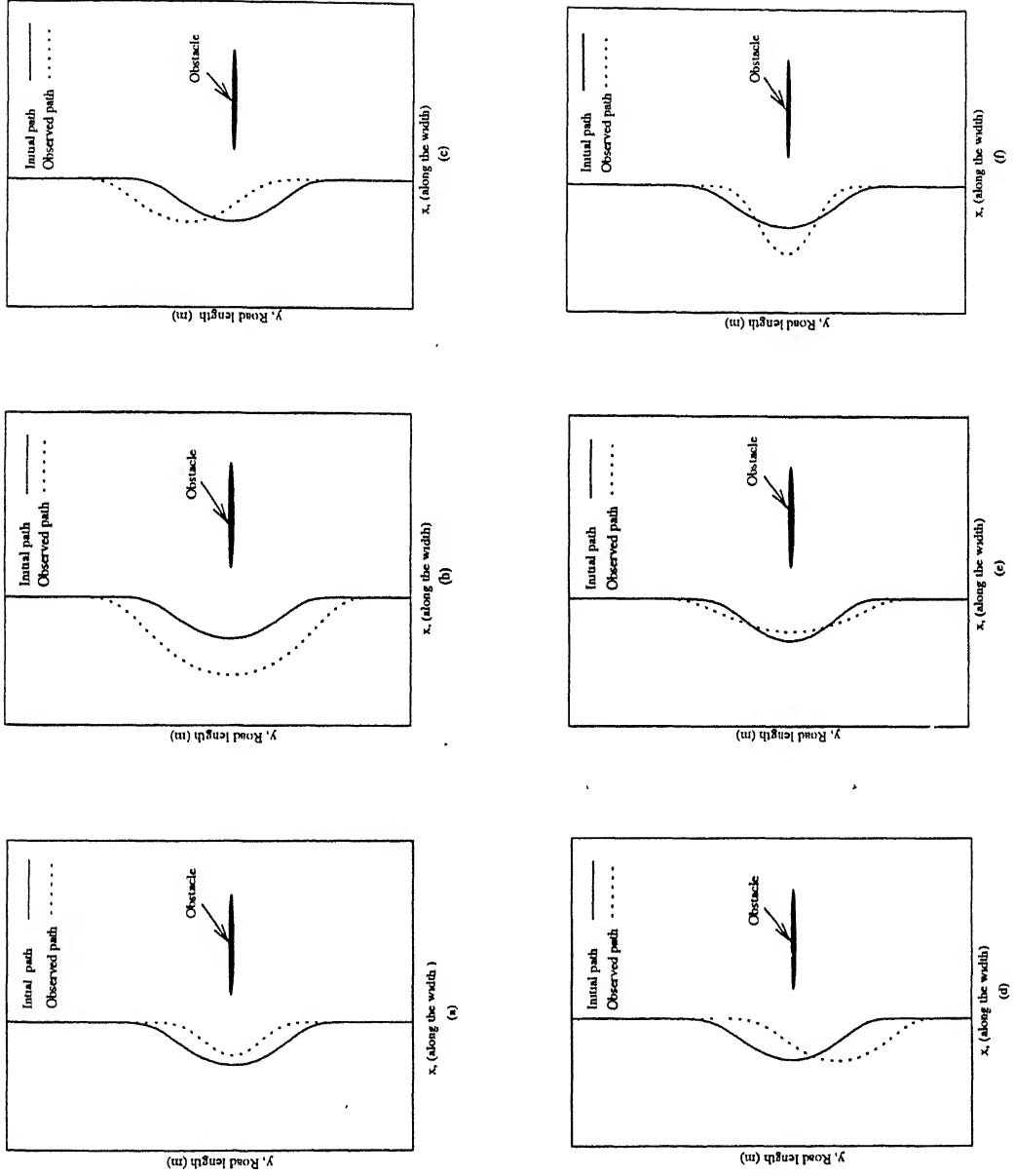


Figure 4.5: Classification of the comparison of the predicted path (after Stage I calibration) and the observed path

Situation 6 which is the opposite of Situation 5.

It may be pointed out here that from the standpoint of determining the rules of the calibration, there exists no difference between the situations shown in Figure 4.5 and their mirror images about a longitudinal axis. In the next section the rules for calibration for each of these situation are developed.

### Rules of calibration

Here, the rules of calibration for the different situations are described. These rules are obtained from the understanding of the effect of different parameters on predicted path (see Chapter 3).

**Situation 1:** The rules are— (i) decrease  $a_4$ , (ii) decrease  $m_a$ , (iii) increase  $b_4$ ,  $b_5$  and ordinate of  $tp$  such that the slope function  $f(y)$  takes a value greater than the initial value in every section, and (iv) if maximum error in upper segment,  $\epsilon_{max}^u$ , is more than that in lower segment,  $\epsilon_{max}^l$ , then decrease the abscissa value of  $tp$  and vice versa. Further, in this situation the rate of change of each parameter is kept same as them are equally effective in reducing in type of error seen in this situation. If however,  $\epsilon_{max}^u > \epsilon_{max}^l$  then  $b_5$  is change at a higher rate than  $b_4$  and vice versa.

**Situation 2:** The rules are— (i) increase  $a_4$ , (ii) increase  $m_a$ , (iii) decrease  $b_4$ ,  $b_5$  and ordinate of  $tp$  such that the slope function  $f(y)$  takes a value smaller than the initial value in every section, and (iv) if maximum error in upper segment,  $\epsilon_{max}^u$ , is more than that in lower,  $\epsilon_{max}^l$ , then decrease the abscissa value of  $tp$  and vice versa. Further, in this situation the rate of change of each parameter is kept same as them are equally effective in reducing in type of error seen in this situation. if however,  $\epsilon_{max}^u > \epsilon_{max}^l$  then  $b_5$  is change at a higher rate than  $b_4$  and vice versa.

**Situation 3:** Unlike in Situation 1 and 2 simple rules for changing the parameter like  $a_4$ ,  $m_a$ ,  $b_4$ ,  $b_5$  and  $tp$  are not possible in this case. The reason for this is that the initial path's differences from the observed path have different characteristics in different segment. For example, the initial path has higher transverse deviation in the upstream side of obstacle but has lower transverse deviation in downstream side of obstacle when compare to observed path. Hence in this case the rules becomes slightly more complex. In following enumerated paragraphs the rules are described.

- (i) In every iteration change  $m_a$  and  $a_4$  in a manner such that the total absolute error (as explained in Section 5.14) reduces in that iteration.

- (ii) Increase  $b_4$  and decrease  $b_5$  so that eventually the value of  $f(y)$  is lower than initial value in the region where transverse deviation of initial path is lower than the observed path and vice versa.
- (iii) Change the abscissa value of  $tp$  such that total absolute error reduces. The ordinate of  $tp$  is changed based on two factors (i) which of  $|\epsilon_{max}^u|$  and  $|\epsilon_{max}^l|$  is greater, and (ii) whether the greater of the has a negative or a positive sign. If the greater of has a positive sign then reduce the ordinate of  $tp$ , if however, it has a negative sign then the ordinate of  $tp$  is increased.

Since parameter  $a_4$  and  $m_a$  change the predicted path symmetrically with respect to transverse axis going through obstacle changes in these parameter play a small rule in reducing total absolute error. Hence in this situation parameter related to  $f(y)$  are changed at a higher rate than  $a_4$  and  $m_a$ .

**Situation 4:** Unlike in Situation 1 and 2 simple rules for changing parameter like  $a_4$ ,  $m_a$ ,  $b_4$ ,  $b_5$  and  $tp$  are not possible in this case. The reason for this is that the initial path's differences from the observed path have different characteristics in different segment. For example, the initial path has higher transverse deviation in the downstream side of obstacle but has lower transverse deviation in upstream side of obstacle when compare to observed path. Hence in this case the rules becomes slightly more complex. In following enumerated paragraphs the rules are described.

- (i) In every iteration change  $m_a$  and  $a_4$  in a manner such that total absolute error (as explained in section 5.14) reduces in that iteration.
- (ii) Decrease  $b_4$  and increase  $b_5$  so that eventually the value of  $f(y)$  is lower than the initial value in the region where transverse deviation of initial path is lower than the observed path and vice versa.
- (iii) Change the abscissa value of  $tp$  such that total absolute error reduces. The ordinate of  $tp$  is change based on two factors (i) which of  $|\epsilon_{max}^u|$  and  $|\epsilon_{max}^l|$  is greater, and (ii) whether the greater of the has a negative or a positive sign. If the greater has a positive sign then reduce the ordinate of  $tp$ , if however, it has a negative sign then ordinate of  $tp$  is increased.

Since parameter  $a_4$  and  $m_a$  change the predicted path symmetrically with respect to transverse axis going through obstacle changes in these parameter play a small rule in reducing total absolute

error. Hence in this situation parameter related to  $f(y)$  are changed at a higher rate than  $a_4$  and  $m_a$ .

**Situation 5:** The rules are– (i) decrease  $a_4$  (since maximum transverse deviation of initial path is more than of observed path), (ii) increase  $m_a$  (because longitudinal deviation of initial path,  $\delta_{in}$  is less than longitudinal deviation of observed path,  $\delta_{obs}$ ), (iii) move the abscissa of  $tp$  in the direction of ordinate value of the point of maximum transverse deviation of the observed path, (iv) change  $b_4$ ,  $b_5$  and ordinate value of  $tp$  such that total error reduces.

Since parameter  $m_a$  is more effective in reducing the type of error seen in this situation. Hence in this situation  $m_a$  is changed at higher rate than the other parameters.

**Situation 6:** The rules are– (i) increase  $a_4$  (since maximum transverse deviation of initial path is less than of observed path), (ii) decrease  $m_a$  (because longitudinal deviation of initial,  $\delta_{in}$  is more than longitudinal deviation of observed path,  $\delta_{obs}$ ), (iii) move the abscissa of  $tp$  in the direction of ordinate value of the point of maximum transverse deviation of observed path, (iv) change  $b_4$ ,  $b_5$  and ordinate value of  $tp$  such that total error reduces.

Since parameter  $m_a$  is more effective in reducing the type of error seen in this situation. Hence in this situation  $m_a$  is changed at higher rate than the other parameters.



# Chapter 5

## RESULTS

In this chapter results are presented to show that the proposed calibration mechanism can successfully calibrated the parameters of the potential functions. Thirteen different cases are studied here. Schematics of these cases are shown in Figure 5.1 as case (a) through case (m). The abscissa of each schematics is the distance along the width of the road from the left edge and the ordinate is the distance along the length of the road. The solid line in the figure is the predicted path from the potential field theory based model of driver behavior before calibration and the broken line is the observed path which can be obtained from real word observations. The solid object in the figure represents the obstacle. The motivation for choosing these cases for studying is that they represent all possible realistic combination of the initial predicted path and observed path.

In the following, the results are shown for each of these thirteen cases. For each of these cases, except for case (m) road width = 6 m, with the left edge assumed at 0 m, obstacle is a circle of diameter 1 m and the center is placed at (50, 3). For case (m) only the placement of the obstacle is different; the center of the obstacle in this case is at (50, 2.3). The results for each case are presented using the following formate. First, a set of two figures marked (a) and (b) are presented. In the figures the solid line represents the path obtained using the potential field theoretical model with an initial (uncalibrated) set of parameter values. The dotted line is a hypothetical path representing (in theory) the observed path (which in practice will be obtained from real world data). The dashed line represents the path obtained using the potential field theoretical model with the calibrated parameter values. The figure marked (a) only presents the initial and observed paths. The figure marked (b) present the initial, observed and calibrated paths.

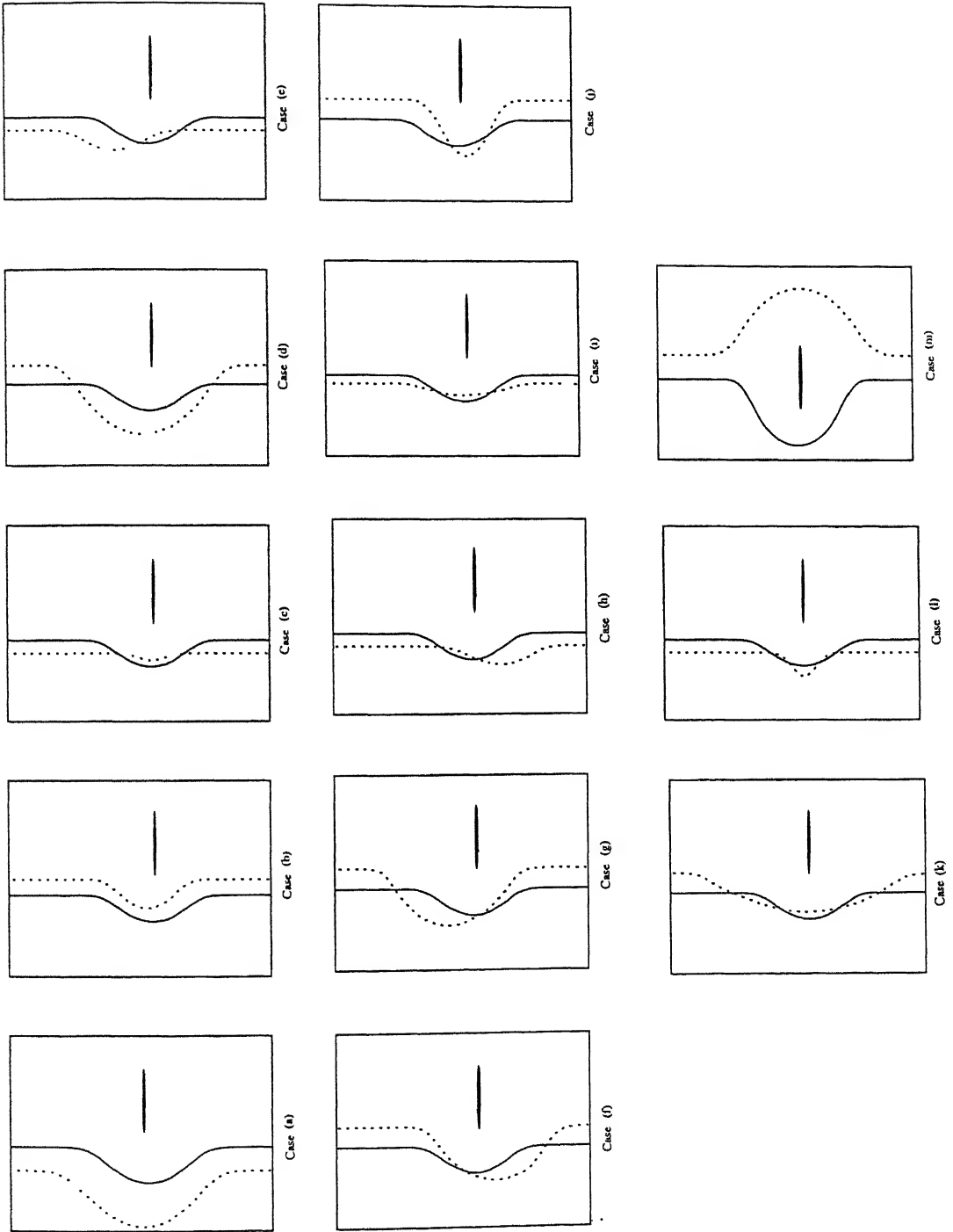


Figure 5.1: Cases studied in this chapter

Second, for each case a table is provided which gives the initial parameter values and the calibrated values.

### 1. Case (a)

Figure 5.2 presents the result obtained using the proposed calibration mechanism. It can be seen from figure that even though there exists reasonable difference between the initial and observed path, after calibration the calibrated path is very close to the observed path. Table 5.1 presents the initial and calibrated values of the parameters of the potential field theory model.

Table 5.1: Initial and calibrated parameter values for Case (a)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	0.9110
$b_1$	0.32641	0.327332
$a_2$	4.0	4.089002
$b_2$	0.04663	0.045745
$a_4$	2.0	3.292
$m_a$	8.0	8.940
$b_4$	2.0	1.952241
$t_1$	0.0	0.0
$\alpha$	0.0	-0.000005
$\beta$	0.0	0.001139
$\gamma$	0.0	-0.071770
$\delta$	2.0	1.952241
$b_5$	2.0	1.640931
$t_2$	100.0	100.0
$tp(x, y)$	(50.0, 2.0)	(42.10, 0.61)

### 2. Case (b)

Figure 5.3 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even though there exists reasonable difference between the initial and observed path, after calibration the calibrated path is very close to the observed path. Table 5.2 presents the initial and calibrated values of the parameters of the potential field theory model.

### 3. Case (c)

Figure 5.4 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even though there exists reasonable difference between the initial

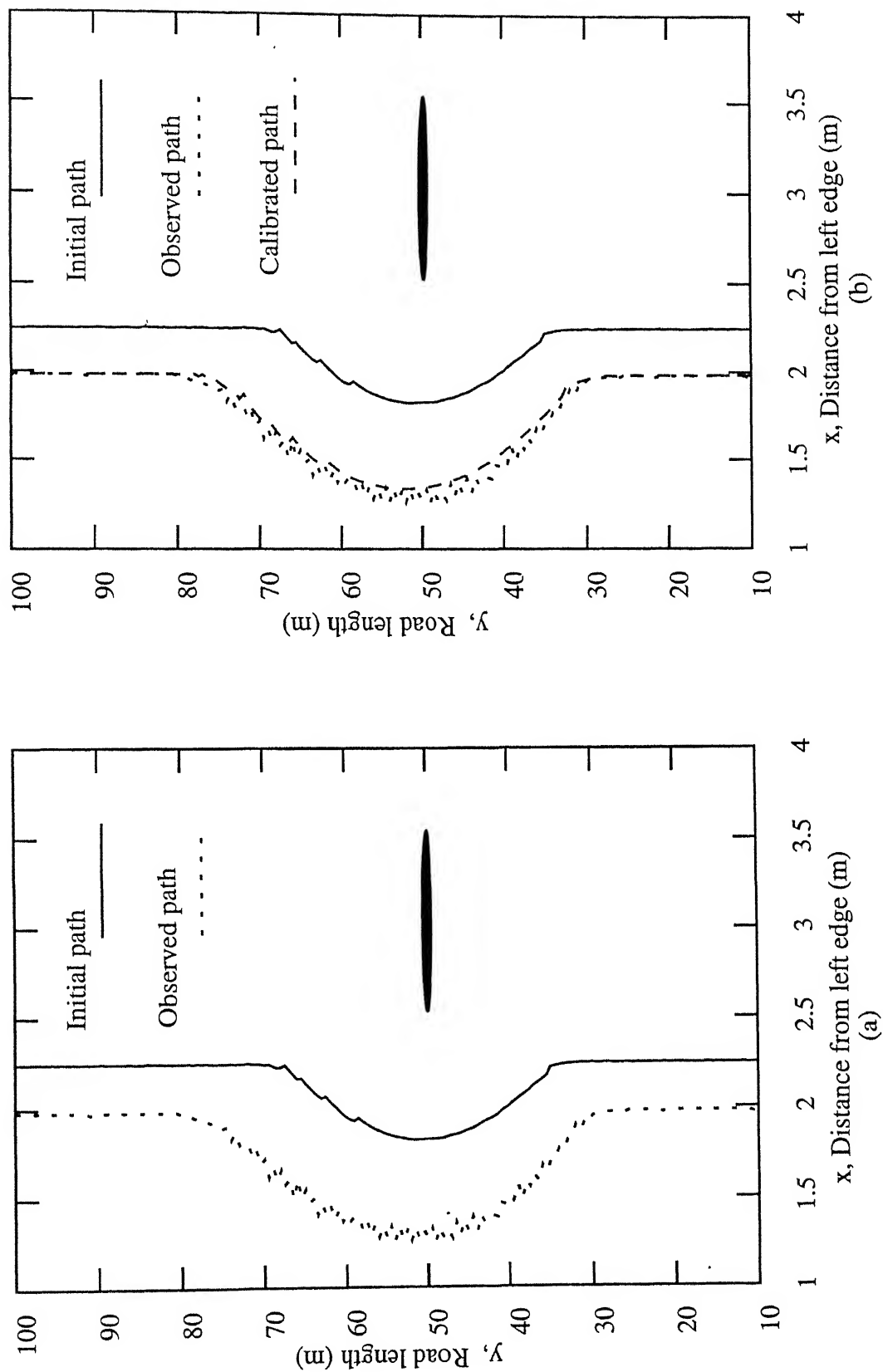


Figure 5.2: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (a)

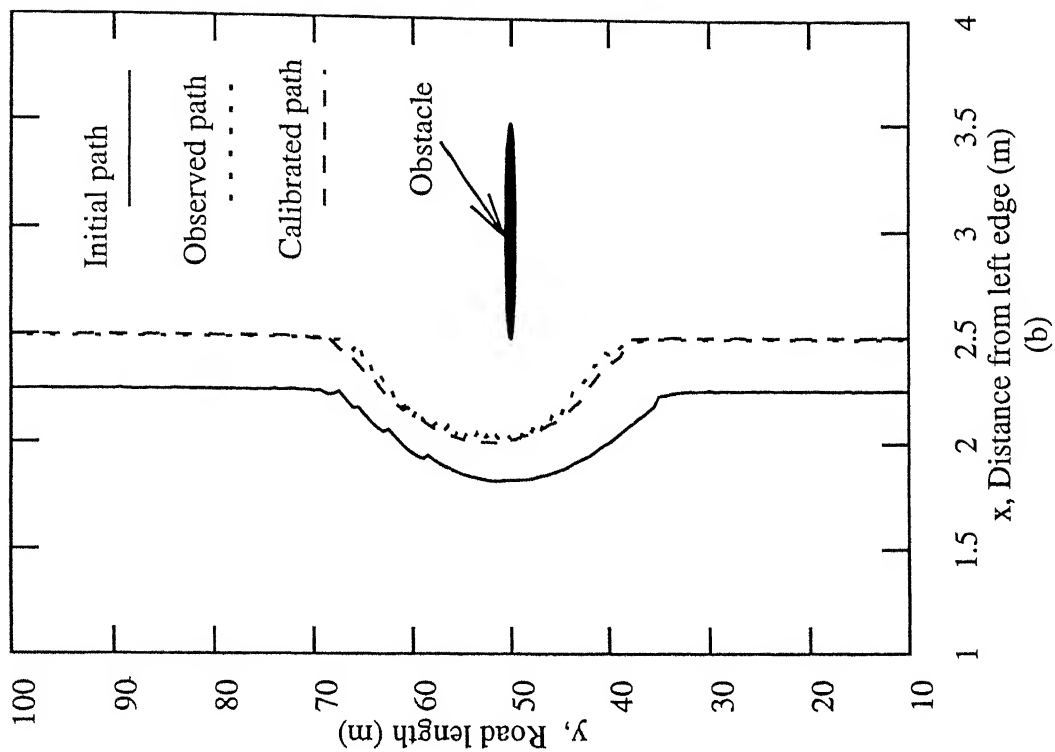
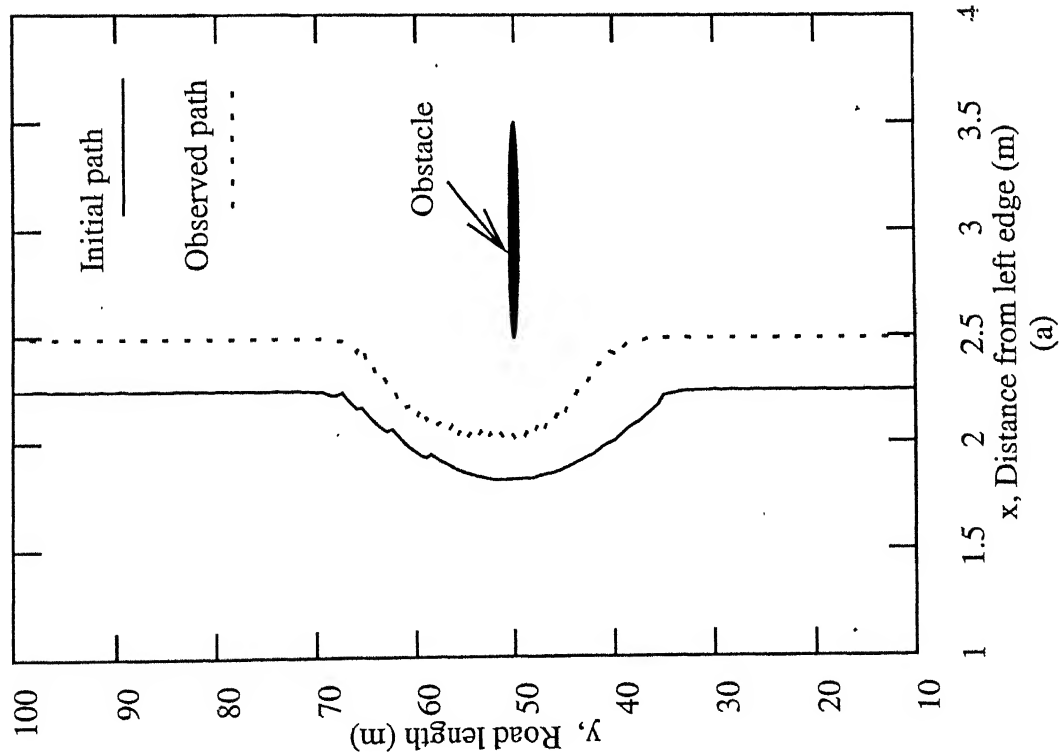


Figure 5.3: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (b)

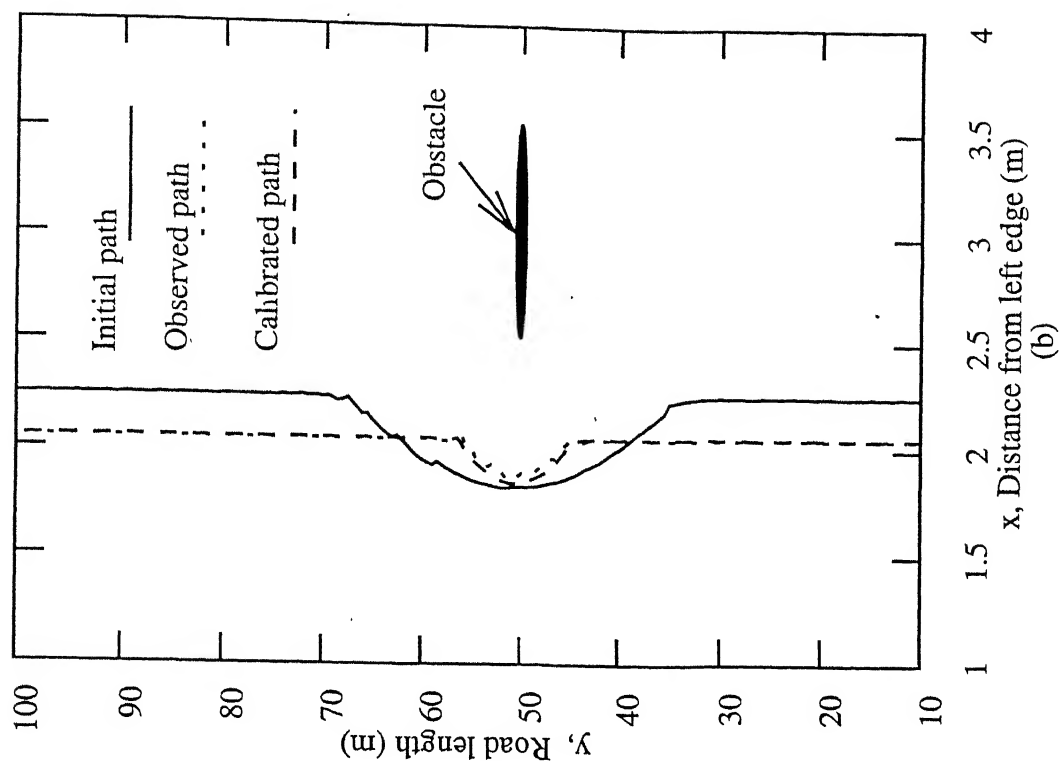
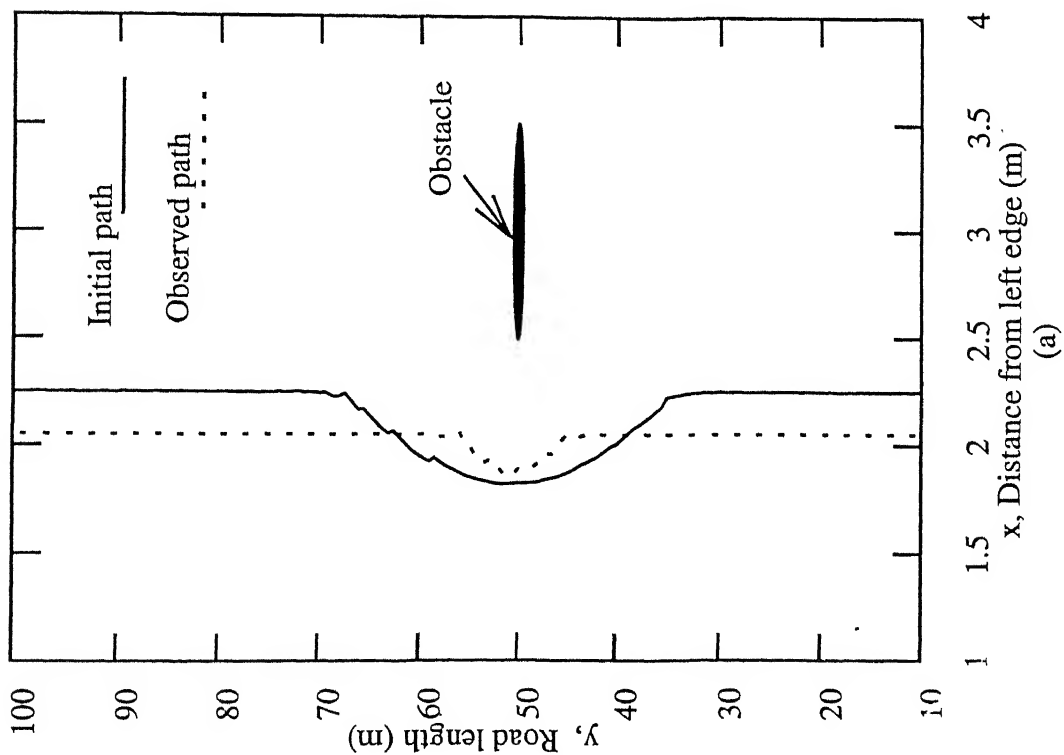


Figure 5.4: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (c)

Table 5.2: Initial and calibrated parameter values for Case (b)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	1.0890
$b_1$	0.32641	0.32553
$a_2$	4.0	3.91100
$b_2$	0.04663	0.047525
$a_4$	2.0	1.65
$m_a$	8.0	7.6500
$b_4$	2.0	2.570301
$t_1$	0.0	0.0
$\alpha$	0.0	-0.000004
$\beta$	0.0	0.000337
$\gamma$	0.0	0.002987
$\delta$	2.0	2.570301
$b_5$	2.0	2.274796
$t_2$	100	100.0
$tp(x, y)$	(50.0, 2.0)	(60.45, 3.10)

and observed path, after calibration the calibrated path is very close to the observed path. Table 5.3 presents the initial and calibrated values of the parameters of the potential field theory model.

Table 5.3: initial and calibrated parameter values for Case (c)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	0.9330
$b_1$	0.32641	0.32712
$a_2$	4.0	4.067002
$b_2$	0.04663	0.045962
$a_4$	2.0	1.3567
$m_a$	8.0	6.3900
$b_4$	2.0	3.729918
$t_1$	0.0	0.0
$\alpha$	0.0	0.0
$\beta$	0.0	0.000648
$\gamma$	0.0	-0.062219
$\delta$	2.0	3.7299918
$b_5$	2.0	3.755372
$t_2$	100.0	100.0
$tp(x, y)$	(50.0, 2.0)	(49.34, 2.21)

#### 4. Case (d)

Figure 5.5 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even though there exists reasonable difference between the initial

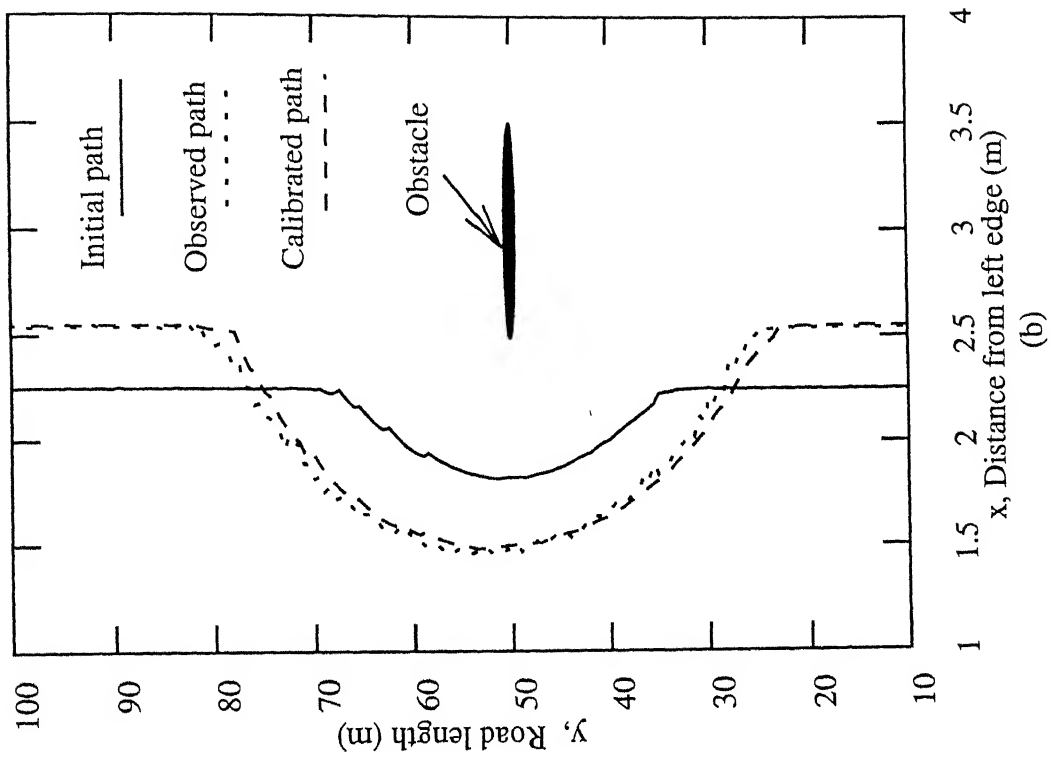
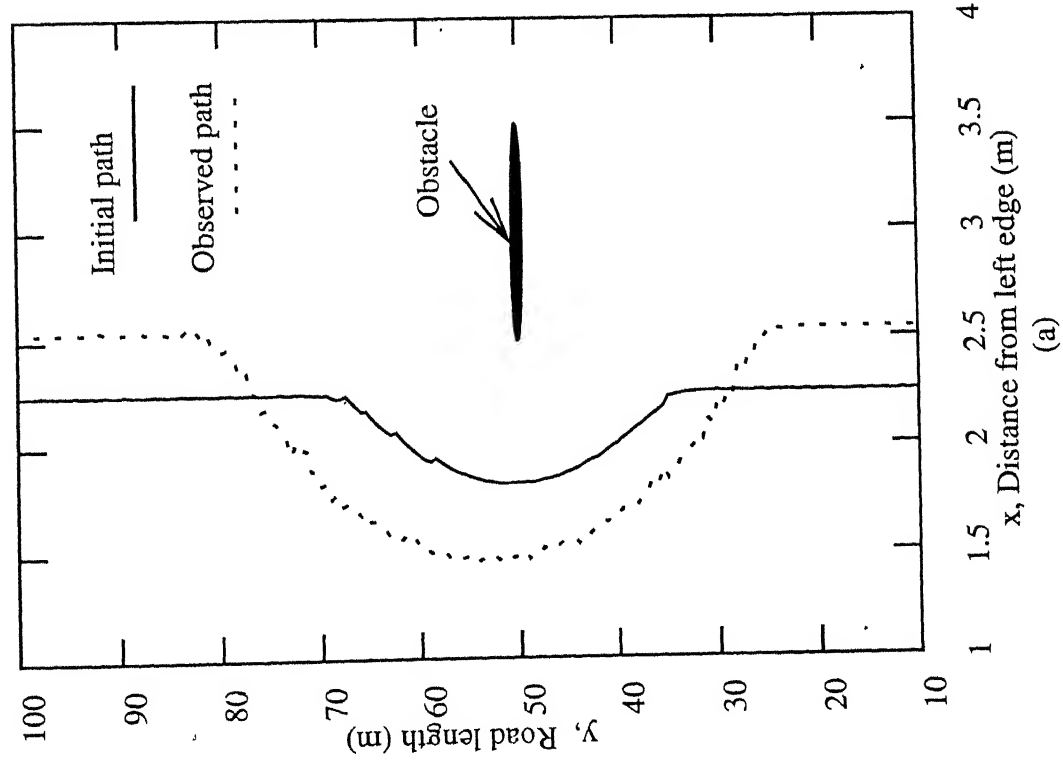


Figure 5.5: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (d)



and observed path, after calibration the calibrated path is very close to the observed path. Table 5.4 presents the initial and calibrated values of the parameters of the potential field theory model.

Table 5.4: Initial and calibrated parameter values for Case (d)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	1.120
$b_1$	0.32641	0.325243
$a_2$	4.0	3.8800
$b_2$	0.04663	0.047835
$a_4$	2.0	3.6440
$m_a$	8.0	9.39992
$b_4$	2.0	1.610029
$t_1$	0.0	0.0
$\alpha$	0.0	-0.000004
$\beta$	0.0	0.000872
$\gamma$	0.0	-0.050558
$\delta$	2.0	1.610029
$b_5$	2.0	1.228277
$t_2$	100.0	100.0
$tp = (x, y)$	(50.0, 2.0)	(40.35, 0.723)

## 5. Case (e)

Figure 5.6 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even though there exists reasonable difference between the initial and observed path, after calibration the calibrated path is very close to the observed path. Table 5.5 presents the initial and calibrated values of the parameters of the potential field theory model.

## 6. Case (f)

Figure 5.7 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even through there exists reasonable difference between the initial and observed path, after calibration the calibrated path is very close to the observed path. Table 5.6 presents the initial and calibrated values of the parameters of the potential field theory model.

## 7. Case (g)

Figure 5.8 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even though there exists reasonable difference between the initial and

Table 5.5: Initial and calibrated parameter values for Case (e)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	0.93300
$b_1$	0.32641	0.32712
$a_2$	4.0	4.067002
$b_2$	0.04663	0.045962
$a_4$	2.0	1.867
$m_a$	8.0	8.950
$b_4$	2.0	3.20001
$t_1$	0.0	0.0
$\alpha$	0.0	0.000021
$\beta$	0.0	-0.002864
$\gamma$	0.0	0.071480
$\delta$	2.0	3.200001
$b_5$	2.0	3.11968
$tp$	100.0	100.0
$tp(x, y)$	(50.0, 2.0)	(15.0, 3.7)

Table 5.6: Initial and calibrated parameter values for Case (f)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	1.120
$b_1$	0.32641	0.325243
$a_2$	4.0	3.880
$b_2$	0.04663	0.047835
$a_4$	2.0	2.385
$m_a$	8.0	8.799910
$b_4$	2.0	0.581535
$t_1$	0.0	0.0
$\alpha$	0.0	0.000005
$\gamma$	0.0	0.000182
$\beta$	0.0	-0.005492
$\delta$	2.0	0.581535
$b_5$	2.0	7.107835
$t_2$	100.0	100.0
$tp = (x, y)$	(50.0, 2.0)	(10.40, 0.55)

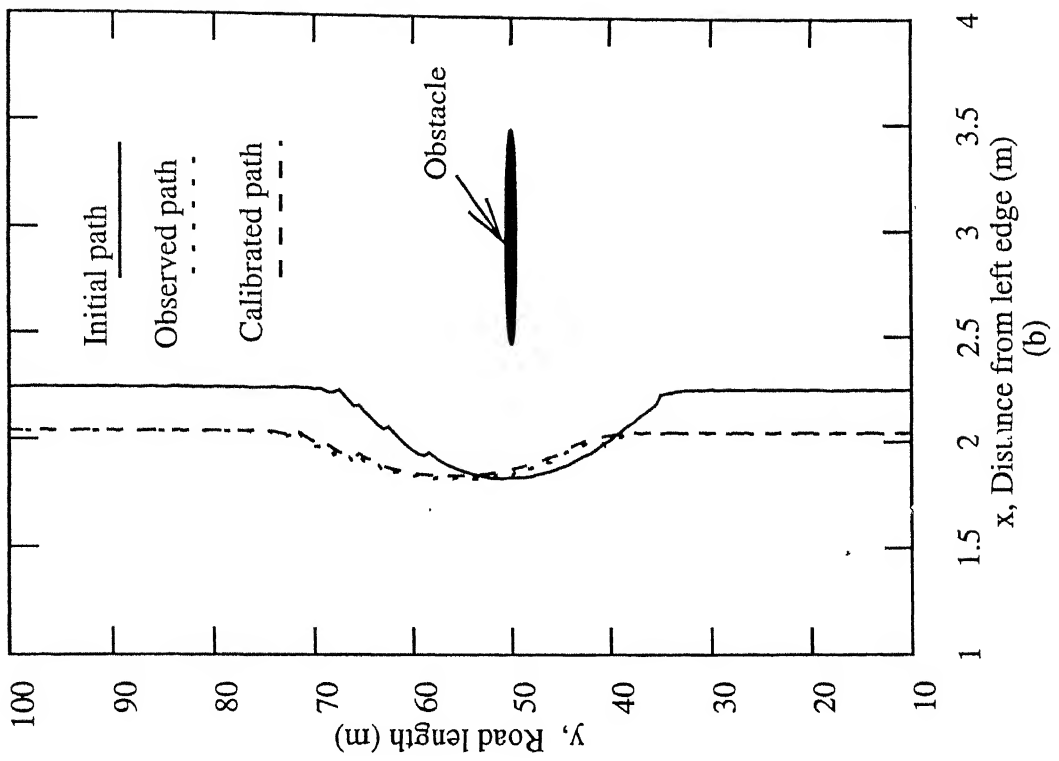
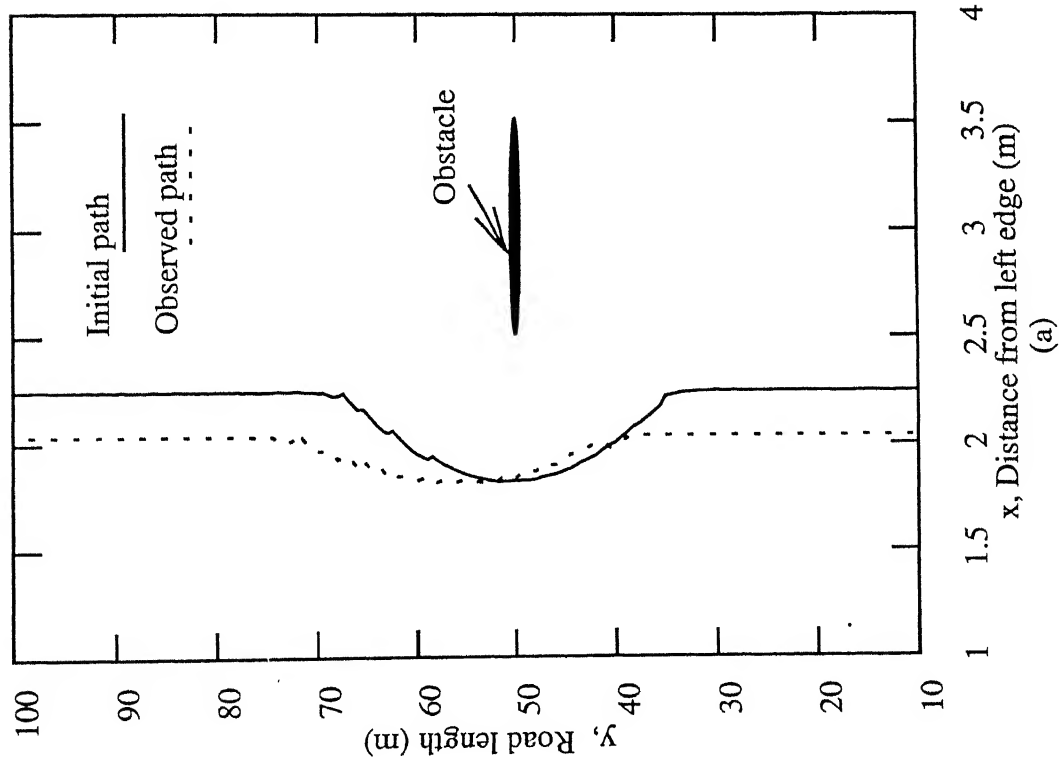


Figure 5.6: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (e)

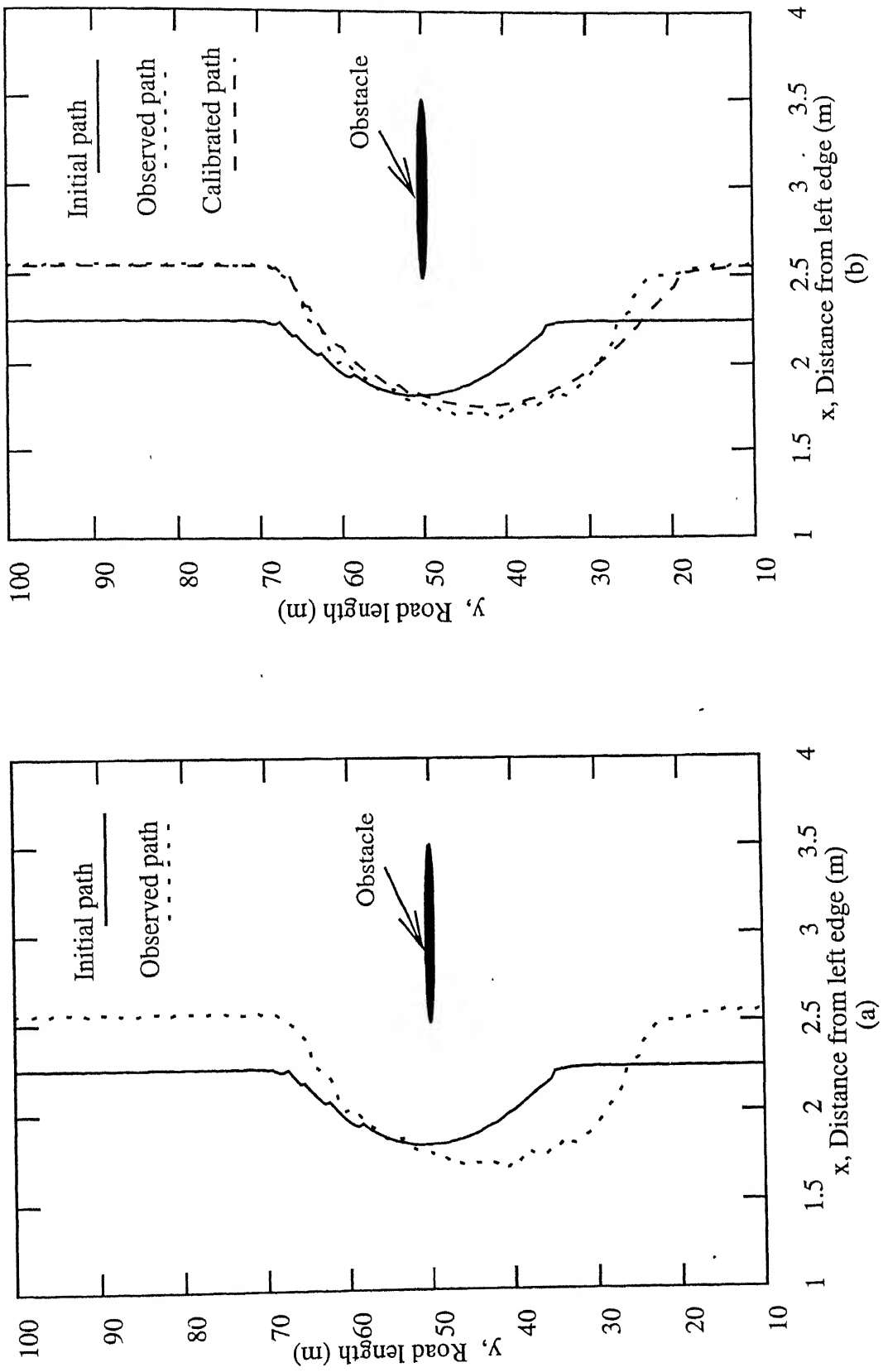


Figure 5.7: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (f)

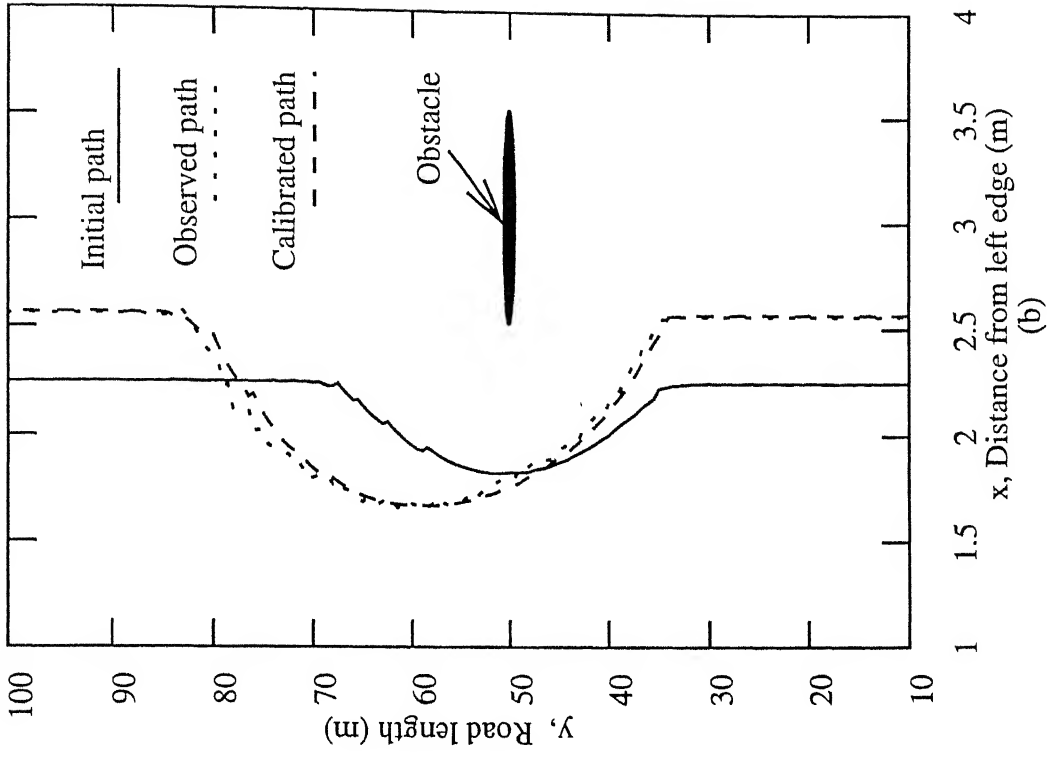
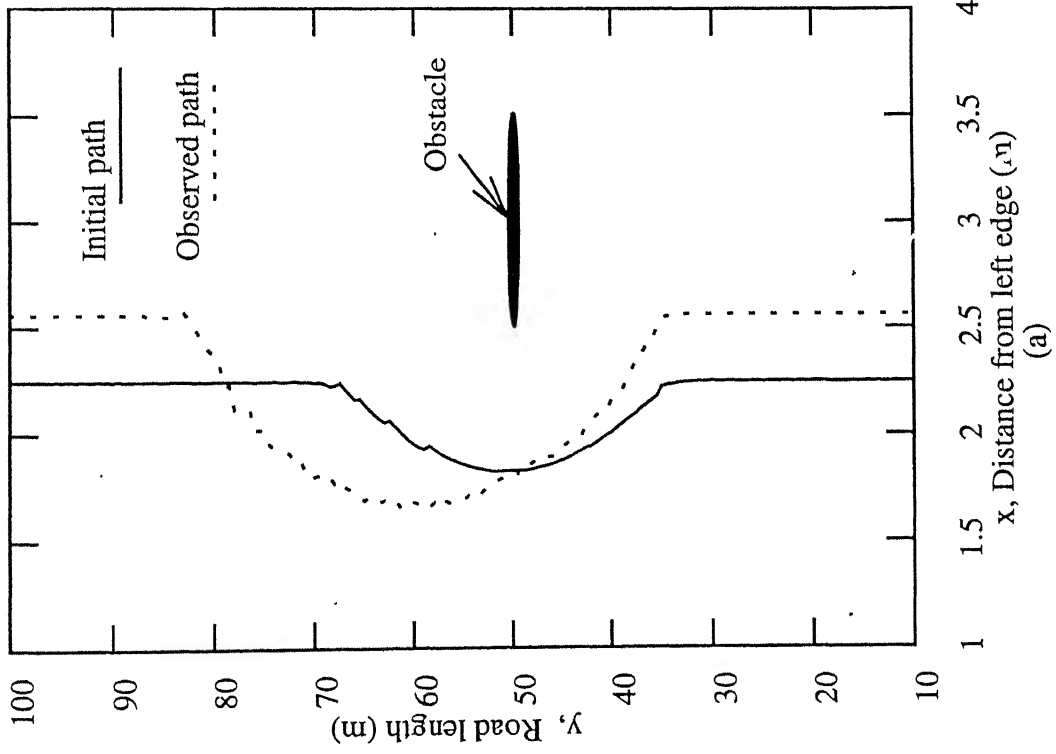


Figure 5.8: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (g)

observed path, after calibration the calibrated path is very close to the observed path. Table 5.7 presents the initial and calibrated values of the parameters of the potential field theory model.

Table 5.7: Initial and calibrated parameter values for Case (g)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	1.120
$b_1$	0.32641	0.325243
$a_2$	4.0	3.8800
$b_2$	0.04663	0.047835
$a_4$	2.0	1.88500
$m_a$	8.0	8.51
$b_4$	2.0	9.162707
$t_1$	0.0	0.0
$\alpha$	0.0	-0.000012
$\beta$	0.0	0.003222
$\gamma$	0.0	-0.289156
$\delta$	2.0	9.162707
$b_5$	2.0	0.703910
$t_2$	100.0	100.0
$tp = (x, y)$	(50.0, 2.0)	(85.10, 0.51)

#### 8. Case (h)

Figure 5.9 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even though there exists reasonable difference between the initial and observed path, after calibration the calibrated path is very close to the observed path. Table 5.8 presents the initial and calibrated values of the parameters of the potential field theory model.

#### 9. Case (i)

Figure 5.10 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even though there exists reasonable difference between the initial and observed path, after calibration the calibrated path is very close to the observed path. Table 5.9 presents the initial and calibrated values of the parameters of the potential field theory model.

#### 10. Case (j)

Figure 5.11 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even though there exists reasonable difference between the initial

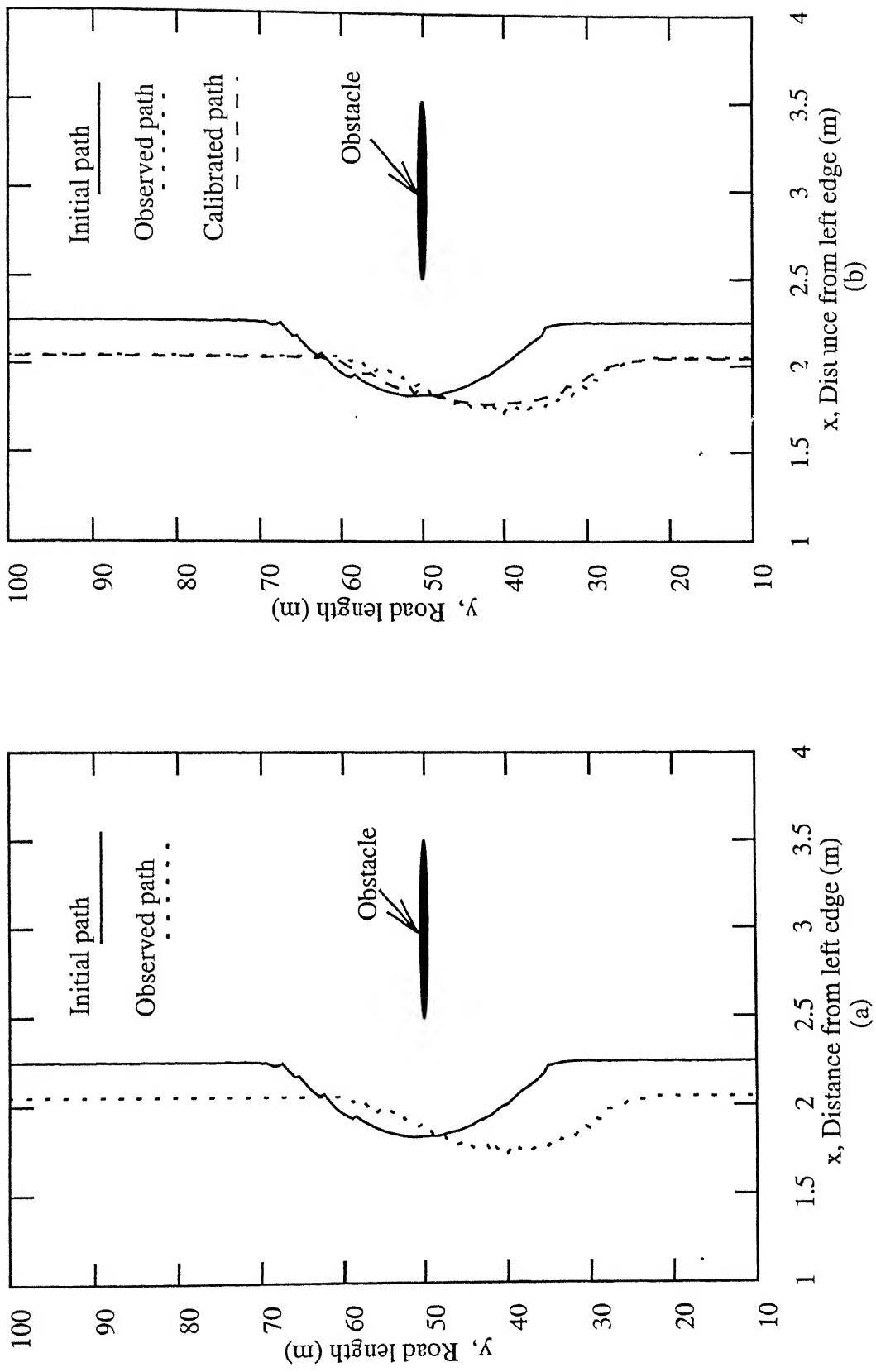


Figure 5.9: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (h)

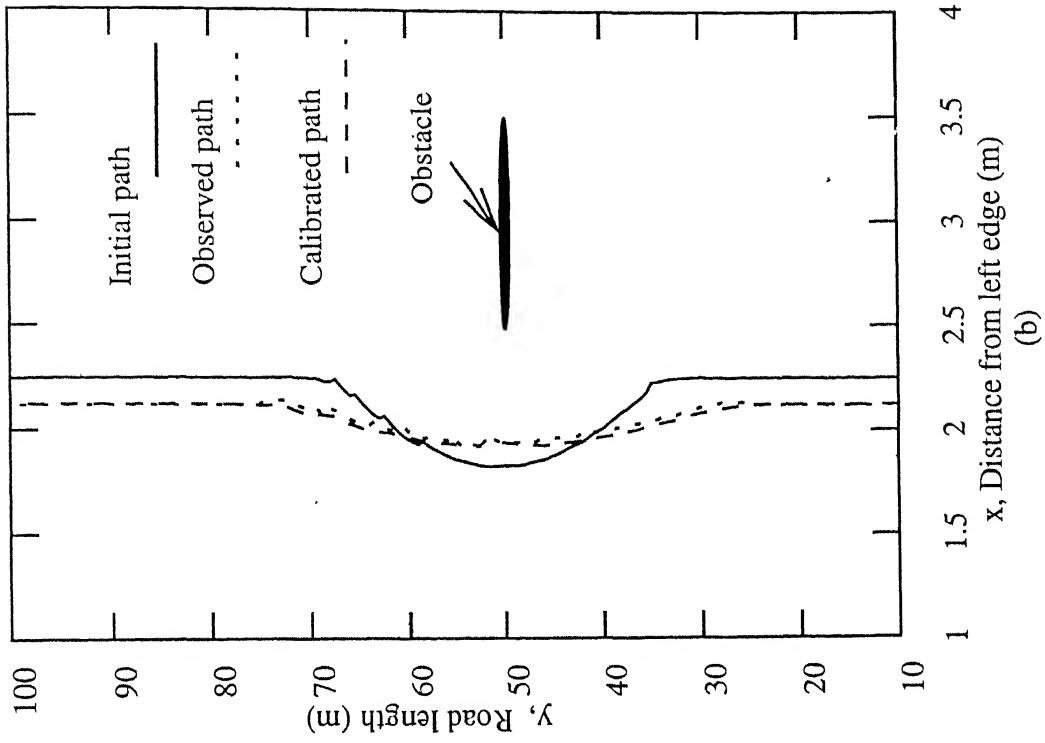
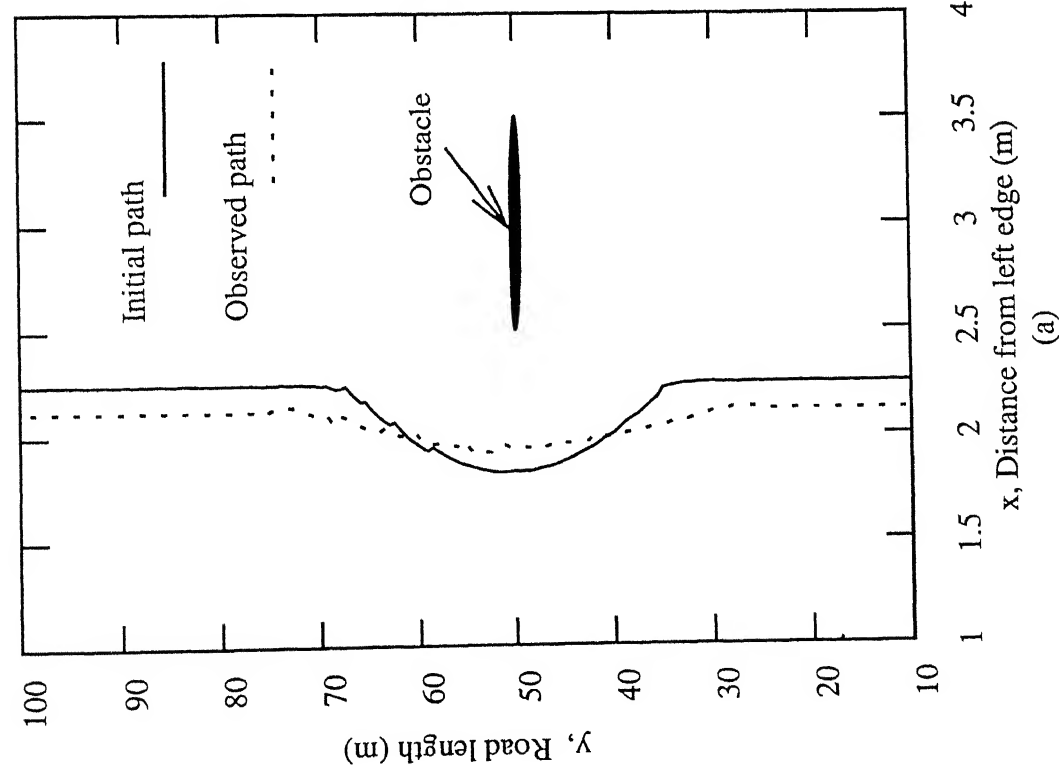


Figure 5.10: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (i)



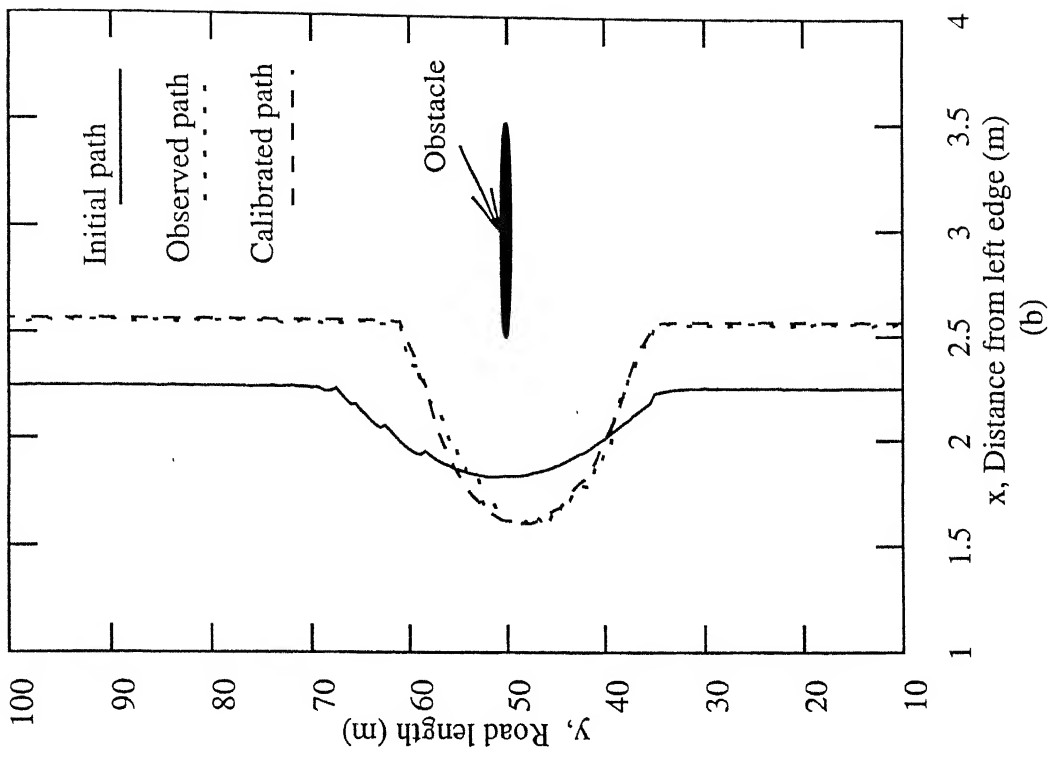
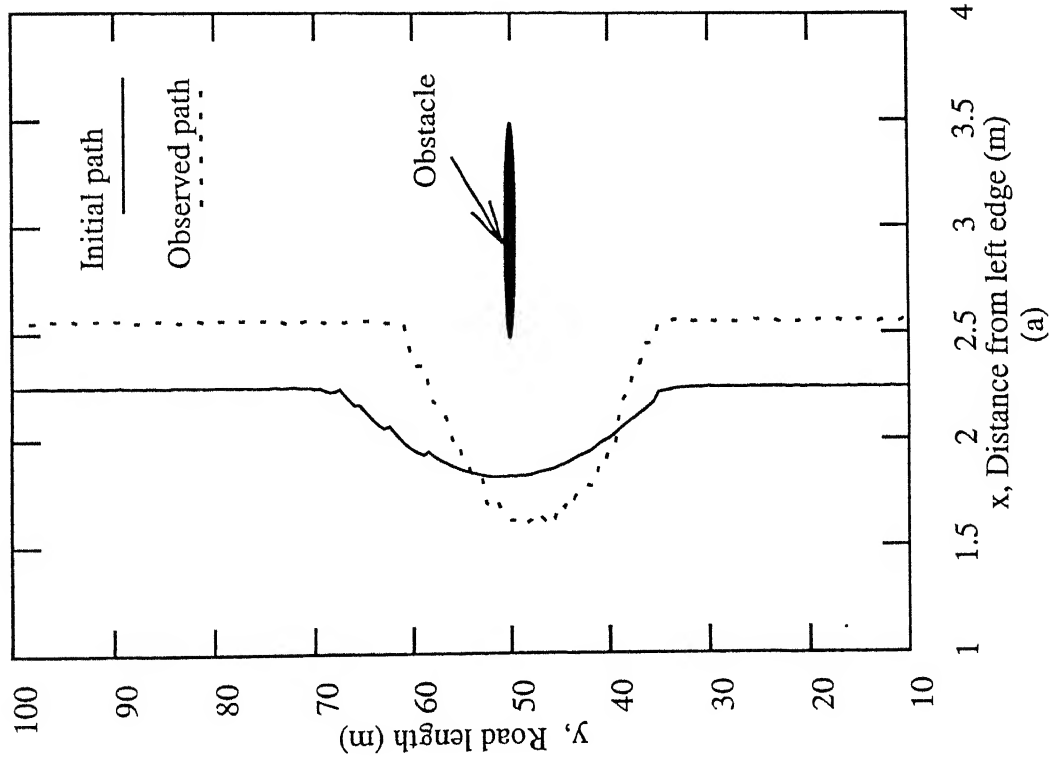


Figure 5.11: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (j)

Table 5.8: Initial and calibrated parameter values for Case (h)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	0.9330
$b_1$	0.32641	0.32712
$a_2$	4.0	4.067002
$b_2$	0.04663	0.045965
$a_4$	2.0	1.899
$m_a$	8.0	8.9500
$b_4$	2.0	2.900171
$t_1$	0.0	0.0
$\alpha$	0.0	-0.000027
$\beta$	0.0	0.004457
$\gamma$	0.0	-0.180238
$\delta$	2.0	2.900171
$b_5$	2.0	2.899993
$t_2$	100.0	2.818590
$tp(x, y)$	(50.0, 2.0)	(85.15, 3.40)

Table 5.9: Initial and calibrated parameter values for Case (i)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	0.95500
$b_1$	0.32641	0.326892
$a_2$	4.0	4.045002
$b_2$	0.04663	0.046185
$a_4$	2.0	1.867
$m_a$	8.0	12.54
$b_4$	2.0	1.30
$t_1$	0.0	0.0
$\alpha$	0.0	0.0
$\beta$	0.0	-0.000517
$\gamma$	0.0	0.049223
$\delta$	2.0	1.300001
$b_5$	2.0	1.30279
$t_2$	100.0	100.0
$tp(x, y)$	(50.0, 2.0)	(49.36, 2.5)

and observed path, after calibration the calibrated path is very close to the observed path. Table 5.10 presents the initial and calibrated values of the parameters of the potential field theory model.

Table 5.10: Initial and calibrated parameter values for Case (j)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	1.12
$b_1$	0.32641	0.325243
$a_2$	4.0	3.8800
$b_2$	0.04663	0.047835
$a_4$	2.0	4.94300
$m_a$	8.0	5.09910
$b_4$	2.0	2.79625
$t_1$	0.0	0.0
$\alpha$	0.0	-0.000001
$\beta$	0.0	0.001339
$\gamma$	0.0	-0.101512
$\delta$	2.0	2.79625
$b_5$	2.0	4.74830
$t_2$	100.0	100.0
$tp(x, y)$	(50.0, 2.0)	(40.21, 0.796)

#### 11. Case (k)

Figure 5.12 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even though there exists reasonable difference between the initial and observed path, after calibration the calibrated path is very close to the observed path. Table 5.11 presents the initial and calibrated values of the parameters of the potential field theory model.

#### 12. Case (l)

Figure 5.13 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even though there exists reasonable difference between the initial and observed path, after calibration the calibrated path is very close to the observed path. Table 5.12 presents the initial and calibrated values of the parameters of the potential field theory model.

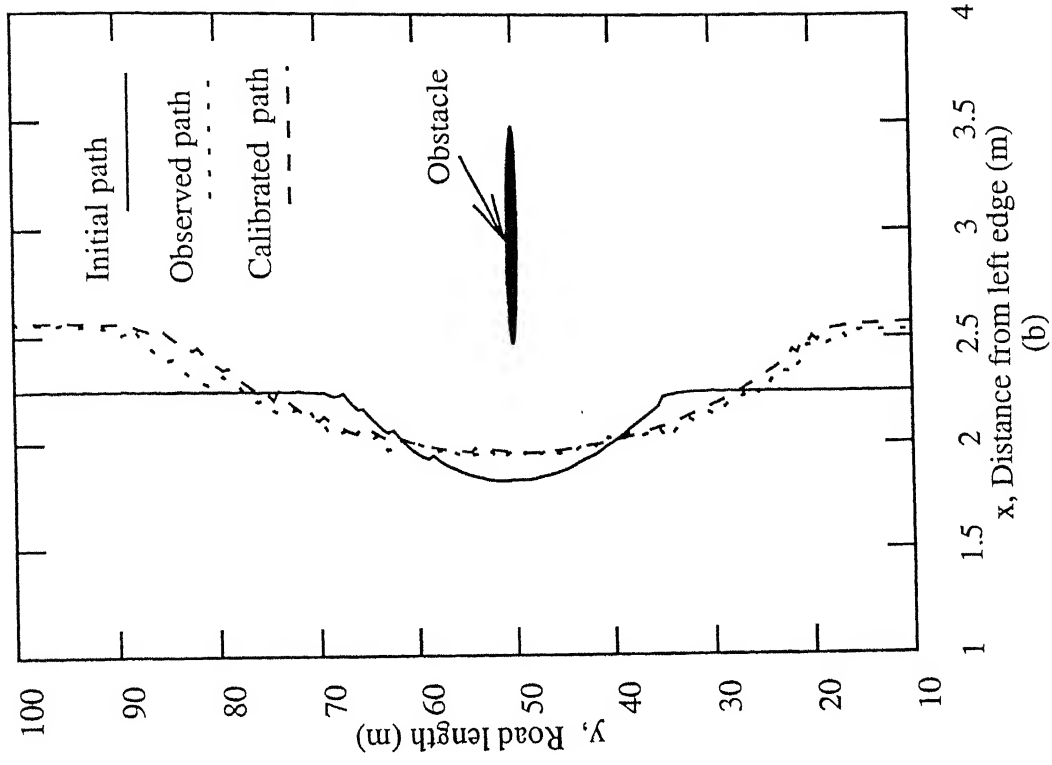
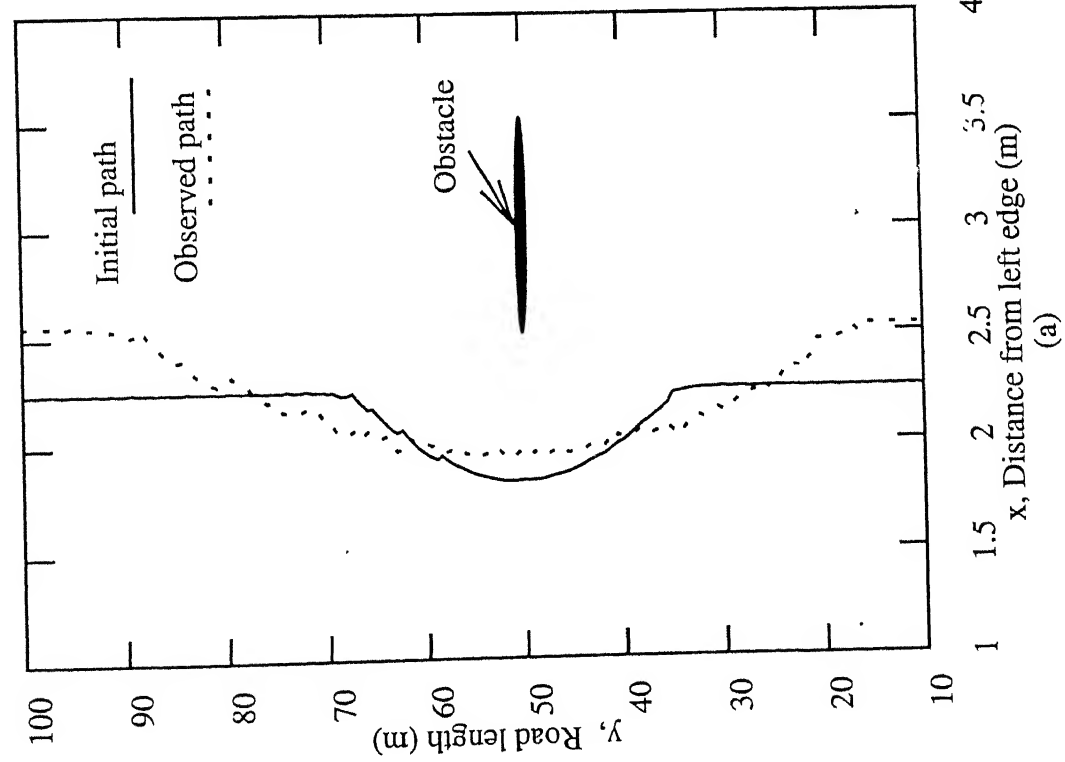


Figure 5.12: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (k)

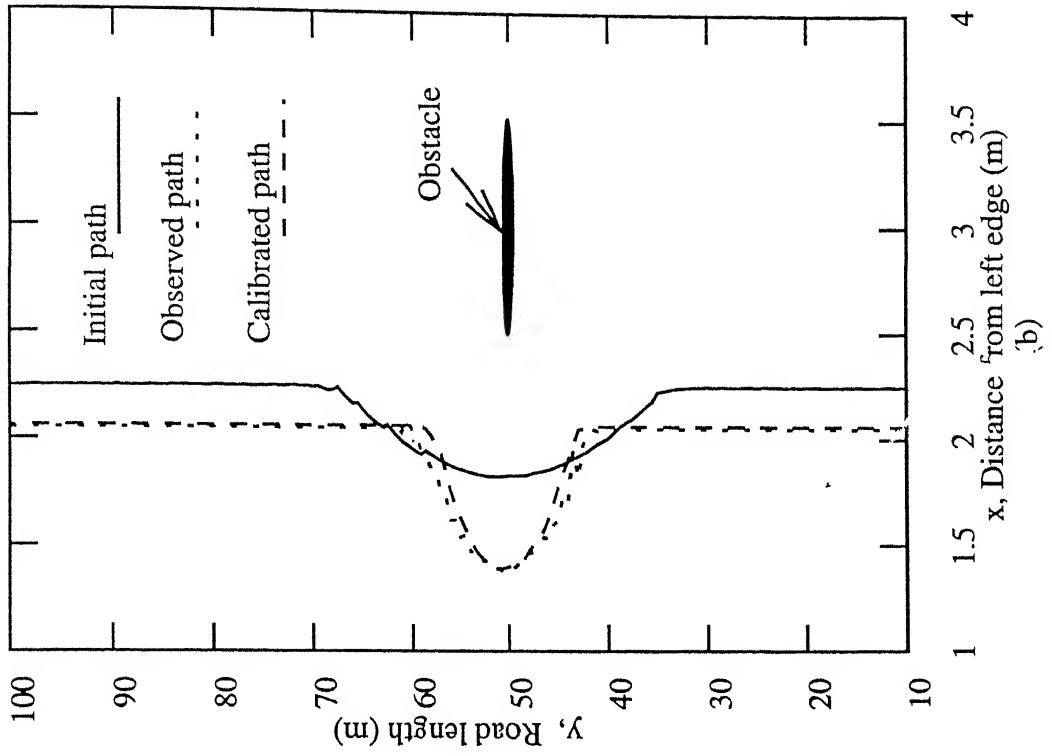
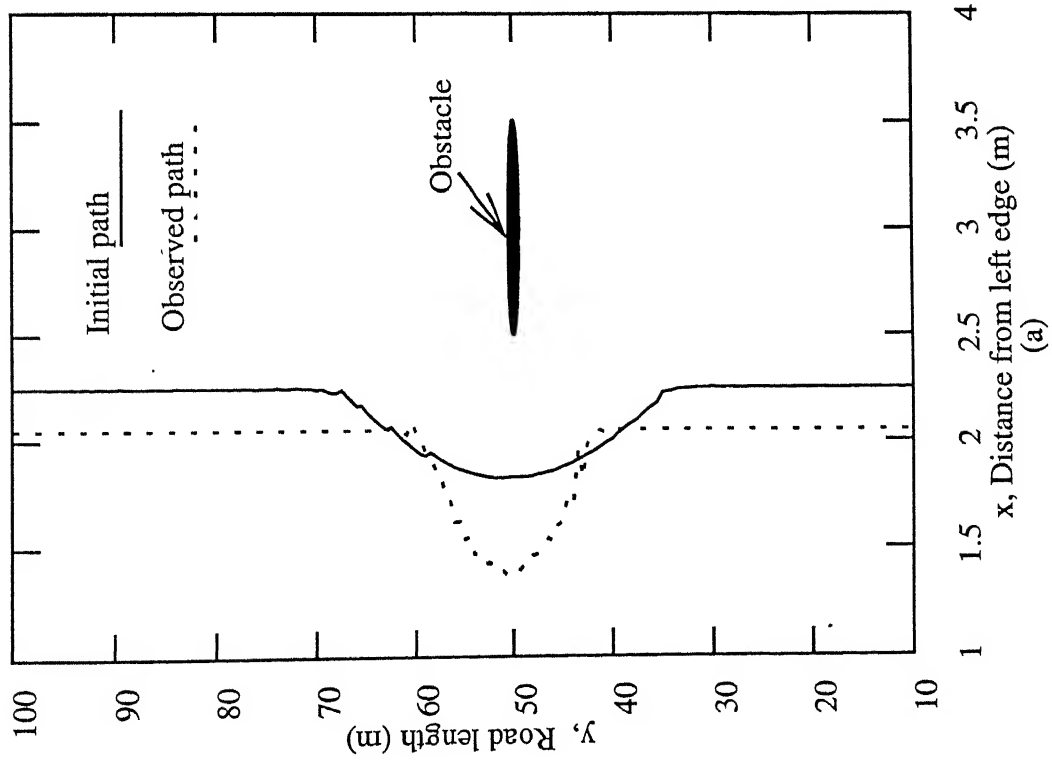


Figure 5.13: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (I)

Table 5.11: Initial and calibrated parameter values for Case (k)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	1.120
$b_1$	0.32641	0.325243
$a_2$	4.0	3.8800
$b_2$	0.04663	0.427835
$a_4$	2.0	1.885
$m_a$	8.0	13.98600
$b_4$	2.0	1.490010
$t_1$	0.0	0.0
$\alpha$	0.0	0.000002
$\beta$	0.0	-0.000610
$\gamma$	0.0	0.039099
$\delta$	2.0	1.490010
$b_5$	2.0	1.361133
$t_2$	100.0	100.0
$tp = (x, y)$	(50.0, 2.0)	(40.25, 2.21)

Table 5.12: Initial and calibrated parameter values for Case (l)

Parameters of the potential functions	Parameter values	
	Initially assumed	After calibration
$a_1$	1.0	0.9330
$b_1$	0.32641	0.32712
$a_2$	4.0	4.067002
$b_2$	0.04663	0.045962
$a_4$	2.0	4.0200
$m_a$	8.0	4.3900
$b_4$	2.0	1.96097
$t_1$	0.0	0.0
$\alpha$	0.0	0.000001
$\beta$	0.0	0.000372
$\gamma$	0.0	-0.045790
$\delta$	2.0	1.960979
$b_5$	2.0	2.07192
$t_2$	100.0	100.0
$tp (x, y)$	(50.0, 2.0)	(51.34, 0.721)

### 13. Case (m)

Figure 5.14 presents the result obtained using the proposed calibration mechanism. It can be seen from the figure that even though there exists reasonable difference between the initial and observed path, after calibration the calibrated path is very close to the observed path. Table 5.13 presents the initial and calibrated values of the parameters of the potential field theory model.

Table 5.13: Initial and calibrated parameter values for Case (m)

Parameters of the potential functions	Parameters values	
	Initially assumed	After calibration
$a_1$	1.0	2.8499
$b_1$	0.32641	0.806805
$a_2$	4.0	3.45001
$b_2$	0.04663	0.121544
$a_4$	2.0	3.420
$m_a$	8.0	9.2100
$b_4$	2.0	1.57306
$t_1$	0.0	0.0
$\alpha$	0.0	0.0
$\beta$	0.0	0.000216
$\gamma$	0.0	-0.024475
$\delta$	2.0	1.57306
$b_5$	2.0	1.56986
$t_2$	100.0	100.0
$tp(x, y)$	(50.0, 2.3)	(51.43, 0.923)

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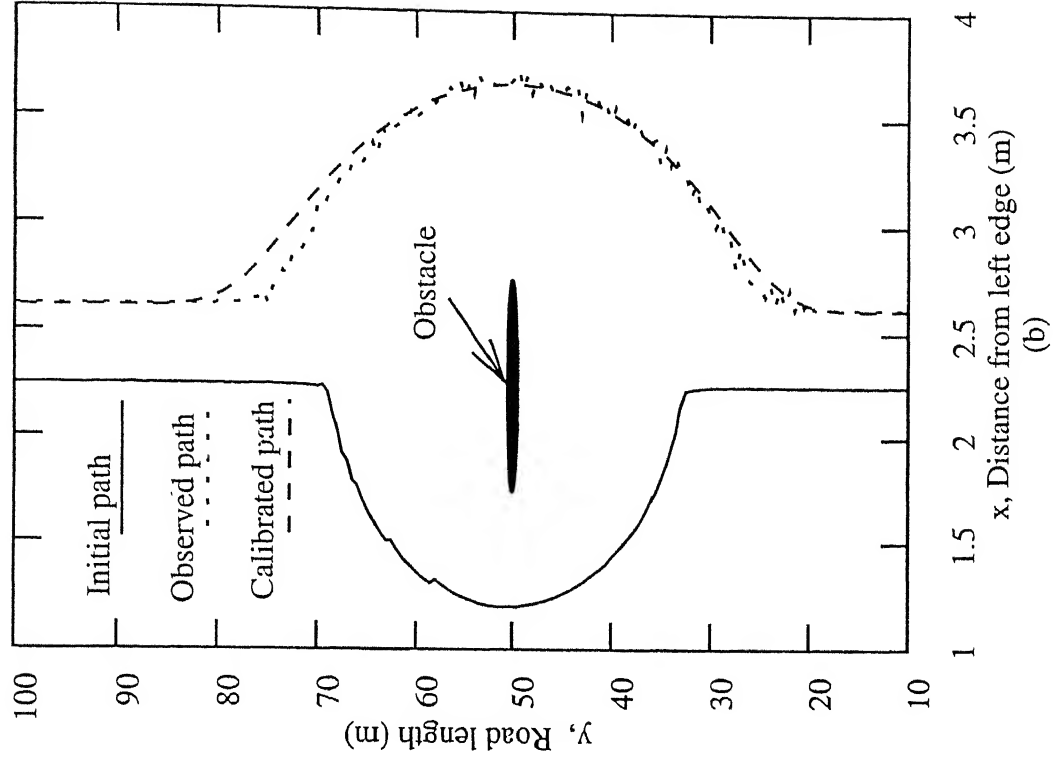
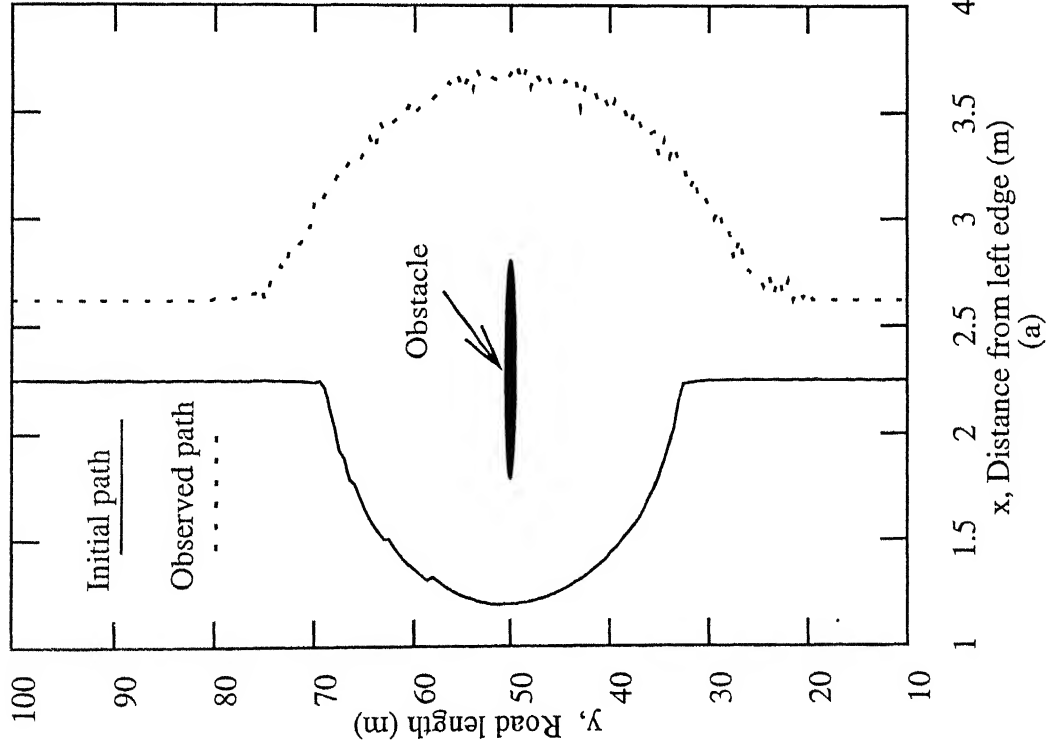


Figure 5.14: Result showing (a) the initial and observed paths and (b) the initial, observed and calibrated paths for Case (m)



## Chapter 6

# CONCLUSIONS

In this thesis a calibration mechanism which can calibrate the parameter values of potential field function of road edges and static obstacles is developed. In order to developed this mechanism a detail parametric study of potential field function is under taken and completed. Results showing the efficacy of proposed mechanism in calibrating the parameters are also presented.

Although the proposed mechanism can ably calibrate the parameters it is felt that the efficiency of the algorithm can be further improved. For example, currently the step side for the corrections have been kept small. Although a attempt has been made to determine which parameter in which situation should be changed in larger step sizes, the determination is largely ad hoc. It is felt that a detail study on the step size should be conducted so that the calibrated values can be obtained faster.

Another short coming of this thesis is that the observed paths were generated rather than experimentally obtained. Although it is felt that the proposed calibration algorithm will function equally well even if observed paths are experimentally obtained one can never be cent percent confident.

It also felt the scope of this study should be enlarged to cover dynamic obstacles like moving vehicles. further, no attempt was made to calibrate the parameters of the models developed by Vasishta [2] and Agrawal [1] only the parameters of the potential functions were calibrated. This shortcoming must also be looked into. Also, the calibration was done based only on the observed position profile (i.e., the observed path of the driver) and did not use information on the velocity

profile (i.e., observed velocities of driver). This drawback needs to be rectified.

Finally a study should be conducted to see whether the calibrated potential field function can predict the driver path reasonably well for driving scenarios which are not used in the calibration process. This test is imperative to see whether the calibration process makes meaningful changes to the potential field functions.

# References

- [1] Saurabh Kumar Agrawal. Modelling of Driver Behavior in the presence of other moving vehicles, *M.Tech Thesis*, Indian Institute of Technology, Kanpur, October 2000.
- [2] Kyatham Vasishta. Preliminary Explorations into Modelling of Driver Behaviour, *M.Tech Thesis*, Indian Institute of Technology, Kanpur, July 1999.
- [3] J.C. Latombe. *Robot Motion Planning*. Kluwer Academic Publishers, Boston, 1991.
- [4] Louis A. Pipes. Car Following Models and Fundamental Diagram of Road Traffic. *Transportation Research*, Vol. 1, 1967, pp. 21-29.
- [5] T. W. Forbes, H. J. Zagorski, E. L. Holshouser, and W. A. Deterline. Measurement of Driver Reactions to Tunnel conditions. *Highway Research Board Proceedings*, Vol. 37, 1958, pp. 60-66.
- [6] T. W. Forbes. Human Factor Considerations in Traffic Flow Theory. *Highway Research Record*, No. 15, 1963, pp. 60-66.
- [7] Robert E. Chandler, Robert Herman, and Elliott W. Montroll. Traffic Dynamics: Studies in Car Following. *Operations Research*, Vol. 6, No. 2, 1958, pp. 165-184.
- [8] Robert Herman, Elliott W. Montroll, Renfry B. Potts, Richard W. Rothery. Traffic Dynamics: Analysis of Stability in Car Following. *Operations Research*, Vol. 7, No. 1, 1959, pp. 86-106.
- [9] Robert Herman and Renfrey B. Potts. Single Lane Traffic Theory and Experiment. *Proceedings of the Symposium on the Theory of Traffic Flow*, 1959, pp. 120-146.
- [10] Denos C. Gazis, Robert Herman, and Renfry B. Potts. Car Following Theory of Steady State Flow. *Operations Research*, Vol. 7, No. 4, 1959, pp. 499-505.
- [11] Denos C. Gazis, Robert Herman, and Richard W. Rothery. Nonlinear Follow-the-Leader Models of Traffic Flow. *Operations Research*, Vol. 9, No. 4, 1961, pp. 545-567.

- [12] Thomas H. Rockwell, Ronal L. Ernest, and Albert Hanken. A Sensitivity Analysis of Empirically Derived Car-following Models. *Transportation Research*, Vol. 2, 1968, pp. 363-373.
- [13] Adolf D. May and Hartmut E. M. Keller. Non-Integer Car-Following Models. *Highway Research Record*, No. 199, 1967, pp. 19-32.
- [14] S. Kikuchi. and P. Chakroborty Car-Following Model Based on Fuzzy Inference System, *Transportation Research Record-1365*, TRB, National Research Council, Washington. D. C., 1992, pp. 82-91.
- [15] Partha Chakroborty and Shinya Kikuchi. Evaluation of the General Motors Based Car-Following Models and a Proposed Fuzzy Inference Model, *Transportation Research Part C*, Vol. 7, 1999, pp. 209-235.
- [16] A. Taragin. Driver Behavior as Affected by Objects on Highway Shoulders, *Highway Research Board Proceedings*, Vol. 34, 1955, pp. 453-472.
- [17] R. M. Michaels and L. W. Gozan. Perceptual and Field Factors Causing Lateral Displacement, *Highway Research Record*, No. 25, Highway Research Board, National Research Council, Washington, D.C., 1963.